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6G Wireless Systems: A Vision, Architectural Elements, and Future Directions

LATIF U. KHAN[1], IBRAR YAQOOB[1], (Senior Member, IEEE), MUHAMMAD IMRAN[1,2], (Member, IEEE), ZHU HAN[1,3], (Fellow, IEEE), AND CHOONG SEON HONG[1], (Senior Member, IEEE)

[1]Department of Computer Science and Engineering, Kyung Hee University, Yongin 17104, South Korea
[2]College of Applied Computer Science, King Saud University, Riyadh 11451, Saudi Arabia
[3]Electrical and Computer Engineering Department, University of Houston, Houston, TX 77004, USA

Corresponding author: Choong Seon Hong (cshong@khu.ac.kr)

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ABSTRACT Internet of everything (IoE)-based smart services are expected to gain immense popularity in the future, which raises the need for next-generation wireless networks. Although fifth-generation (5G) networks can support various IoE services, they might not be able to completely fulfill the requirements of novel applications. Sixth-generation (6G) wireless systems are envisioned to overcome 5G network limitations. In this article, we explore recent advances made toward enabling 6G systems. We devise a taxonomy based on key enabling technologies, use cases, emerging machine learning schemes, communication technologies, networking technologies, and computing technologies. Furthermore, we identify and discuss open research challenges, such as artificial-intelligence-based adaptive transceivers, intelligent wireless energy harvesting, decentralized and secure business models, intelligent cell-less architecture, and distributed security models. We propose practical guidelines including deep Q-learning and federated learning-based transceivers, blockchain-based secure business models, homomorphic encryption, and distributed-ledger-based authentication schemes to cope with these challenges. Finally, we outline and recommend several future directions.

INDEX TERMS 6G, 5G, Internet of Things, Internet of Everything, federated learning, meta learning, blockchain.

I. INTRODUCTION

The remarkable upsurge of Internet of everything (IoE)-based smart applications has paved the way for the evolution of existing wireless networks. The term IoE refers to bringing together things, data, people, and process, via emerging technologies to offer a wide variety of smart services [1]. The emerging IoE services include autonomous connected vehicles, brain–computer interfaces, extended reality (XR), flying vehicles, and haptics [2]–[4]. These services are mostly based on ultra-high reliability, high data rates, unmanned mobility management, and long-distance communication. Fifth-generation (5G) wireless networks are envisioned to enable a wide variety of smart IoE-based services. The 5G targeted tactile network is accessed via different approaches, such as simultaneous use of unlicensed and licensed bands, intelligent spectrum management, and 5G new radio, to enable different smart applications [5]–[8]. However, 5G has several inherent limitations and difficulties to completely fulfill its target goals until now. The development of different data-centric, automated processes are proving to exceed the capabilities defined by key performance indicators of 5G [9]. For instance, several applications, such as haptics, telemedicine, and connected autonomous vehicles, are intended to use long packets with ultra-high reliability and high data rates. Such applications violate the notion of generally using short packets for ultra-reliable low-latency communication (URLLC) in 5G [2]. The next generation of virtual and augmented reality-based applications, such as holographic teleportation will require microsecond-level latency and Tbps-level data

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TABLE 1. Comparison of 5G and 6G.

Parameter	5G	6G
Peak data rate	$10 - 20$ Gb/s	$>$ 1Tbps
Spectrum efficiency	$3 \sim 5$x relative to 4G	$>$ 3x relative to 5G
Receiver sensitivity	About -120dBm	< -130dBm
Latency	ms level	$<$ 1ms
Mobility	350 km/h	>1000km/h
Traffic density	$10Tb/s/km^2$	>$100Tb/s/km^2$
Energy efficiency	1000x relative to 4G	10x relative to 5G
Processing delay	100ns	10ns
End-to-end reliability requirements	99.999 percent	99.99999 percent
Radio only delay requirements	100ns	10ns

rates [10]. Such a type of requirements seem difficult to be fulfilled by 5G networks. Furthermore, the 5G connectivity density of $10^6/km^2$ [11] might not be able to meet the growing demands of next-generation smart industries. Therefore, sixth-generation (6G) wireless systems must be developed. 6G will use artificial intelligence (AI) as an integral part that has the capability to optimize a variety of wireless network problems [12]. Typically, mathematical optimization techniques are used to optimize wireless network problems. To solve these mathematical optimization problems, we can use convex optimization schemes, matching theory, game theory, heuristic, and brute force algorithms. However, these solution approaches might suffer from the issue of high complexity which in turn degrades the capacity of a system. Machine learning is capable of optimizing various complex mathematical problems including the problems that cannot be modeled using mathematical equations.

Rethink Technology Ltd. Research indicates several challenges in the deployment of advanced wireless networking technologies: guaranteed robustness, and management and pricing of virtual network functions due to their uncertain nature [13]. Other main problems include fronthaul cost issue and vendor hostility. Although an open interface between remote radio unit and baseband unit has been proposed, the true evolved common public radio interface is difficult to experience. Therefore, a novel 6G architecture must be developed to tackle these challenges. Fig. 1 presents an overview of 6G wireless system and illustrates its key requirements in terms of capacity, uplink data rate, downlink data rate, localization precision, reliability in terms of frame error rate, latency, jitter, and energy per bit [14]. Several enabling technologies and use cases are also illustrated. Furthermore, overview of different wireless mobile technologies with their commencement year and other features is presented in Fig. 2 [15]. On the other hand, comparison of 5G and 6G for different parameters is given in Table 1 [2], [14], [16].

A. 6G MARKET STATISTICS AND RESEARCH ACTIVITIES

Although 5G wireless systems are not fully deployed yet, 6G wireless systems are envisioned by much research to fulfill the needs of expected novel IoE smart services in the foreseeable future. According to statistics, the 6G market will grow at a compound annual growth rate of 70% from 2025 to 2030 and reach 4.1 billion US dollars by 2030 [17]. Among various components of 6G, such as edge computing, cloud computing, and AI, communication infrastructure will offer the largest market share of up to 1 billion US dollars. Another key component of 6G; namely, AI chipsets, will be more than 240 million units in number by 2028.

Different organizations have started 6G projects [18]–[21]. The 6G Flagship research program [18] is supported by the Academy of Finland and led by the University of Oulu to carry out the co-creation of an ecosystem for 6G innovation and 5G adoption. The vision of the 6G flagship program is a data-driven society with unlimited, instant wireless connectivity. Initially, five organizations; namely, VTT Technical Research Center of Finland Ltd., Oulu University of Applied Sciences, Nokia, Business Oulu, and Aalto University, joined the program as collaborators. Later, InterDigital and Keysight Technologies joined the program. An agreement was signed between the South Korean government and the University of Oulu, Finland for the development of 6G technology [19]. Furthermore, LG has established its first research laboratory at the Korea Advanced Institute of Science and Technology to carry out 6G research activities [20]. SK Telecom started joint research on 6G with Samsung, Nokia, and Ericsson [21]. Research on 6G has started in China, as officially announced by the Ministry of Science and Technology [22]. Moreover, the Chinese vendor Huawei has already started 6G research at its research center in Ottawa, Canada [23]. Several 6G research programs have been started in the US, as announced by the US president [24]. Additionally, the NYU WIRELESS research center, which comprises nearly 100 faculty members and graduate students, is working on communication foundations, machine learning, quantum nanodevices, and 6G testbeds [25]. Existing 6G tutorials and surveys are discussed next.

B. EXISTING SURVEYS AND TUTORIALS

Several studies surveyed 6G wireless systems [2], [4], [9], [10], [13], [16], [26]–[29]. Saad *et al.* presented applications, enabling technologies, and few open research challenges [2]. They discussed applications, metrics, and new services for 6G. Moreover, 6G driving trends and performance matrices were presented. Letaief *et al.* presented the vision of AI-empowered 6G wireless networks [4]. They discussed 6G network architecture with key enablers and 6G applications for various AI-enabled smart services. The authors in [26] focused on 6G use cases, enabling technologies, and open research challenges. The study conducted in [9] discussed the evolution of wireless communication systems towards 6G and presented its use cases. Primarily, the authors presented 6G key enabling technologies with their associated challenges and possible applications. Finally, they discussed the integration of intelligence in 6G systems. Another study discussed enabling technologies, architecture, requirements, and key drivers of 6G [13]. The authors in [27]

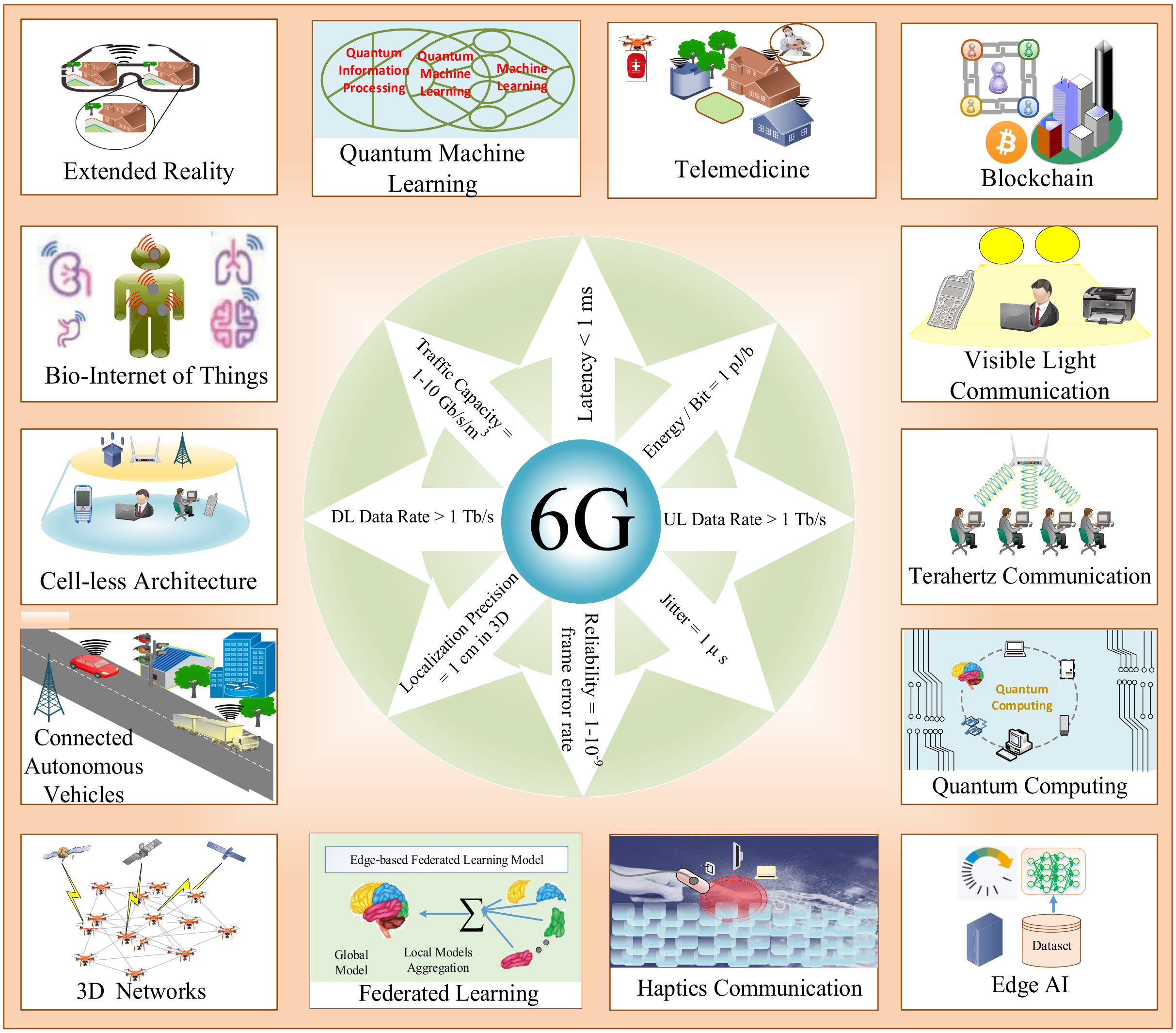

FIGURE 1. 6G wireless systems overview.

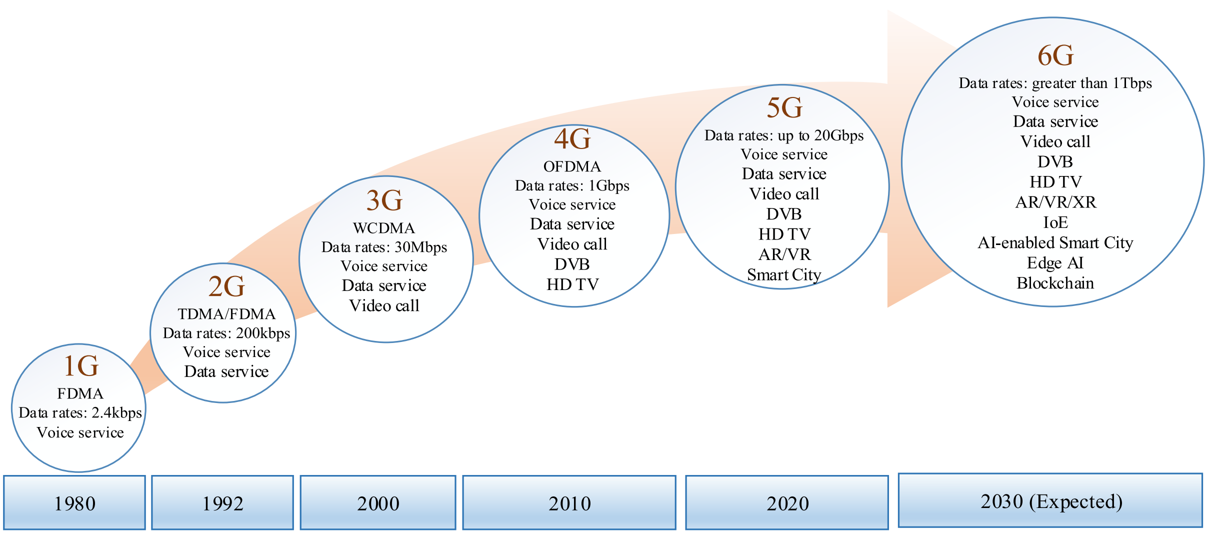

FIGURE 2. Evolution of wireless mobile technologies.

TABLE 2. Summary of the existing surveys and tutorials with their primary focus.

Reference	Recent advances	Taxonomy	Key enabling technologies	Use cases	Remarks
Saad *et al.*, [2]	✗	✗	✓	✓	The tutorial presents applications, enabling technologies, and few open research challenges.
Letaief *et al.*, [4]	✗	✗	✓	✓	The tutorial presents vision, network architecture, and key enablers for 6G.
Tariq *et al.*, [26]	✗	✗	✓	✓	The tutorial discusses use cases, enabling technologies, and open research challenges.
Giordani *et al.*, [9]	✗	✗	✓	✓	The tutorial presents primarily 6G key enabling technologies.
Zong *et al.*, [13]	✗	✗	✓	✗	The tutorial mainly discusses enabling technologies, architecture, requirements, and key drivers of 6G.
Yang *et al.*, [27]	✗	✗	✓	✗	The tutorial provides an overview of 6G based on time-frequency-space resource utilization and key enabling technologies.
Zhang *et al.*, [28]	✗	✗	✓	✓	The tutorial mainly focuses on key enabling technologies and vision of 6G.
Kato *et al.*, [29]	✗	✗	✗	✗	The tutorial mainly focuses on challenges regarding machine learning toward 6G.
Akyildiz *et al.*, [10]	✗	✗	✓	✓	The survey comprehensively discuses enabling technologies, use cases, physical layer modeling, and open research challenges.
Chen *et al.*, [16]	✗	✗	✓	✗	The tutorial presents requirements, applications, technology trends, and open research challenges regarding 6G.
Our Survey	✓	✓	✓	✓	N.A

surveyed potential technologies for 6G wireless networks. First, the authors provided an overview of 6G based on time-frequency-space resource utilization. Second, key techniques for the evolution of wireless networks to 6G are presented. Finally, the authors presented future issues regarding 6G deployment. Zhang *et al.* mainly discussed the key technologies and vision of 6G [28]. The authors discussed the 6G use cases and their requirements in terms of peak data rate, user-experienced data rate, over-the-air latency, energy efficiency, and connectivity density. Kato *et al.* discussed various machine learning schemes and presented 10 challenges regarding intelligentization of 6G wireless systems [29]. Akyildiz *et al.* [10] presented detailed discussions on key enabling technologies for 6G. They presented key performance indicators and use cases of 6G. Terahertz communications with its applications, devices, physical layer modeling, and open problems are discussed in detail. Furthermore, intelligent communication environments with its layered architecture are described. Finally, several open research challenges are presented. Chen *et al.* presented vision, requirements, applications, and technology trends in 6G [16]. Furthermore, they discussed open research challenges and orbital angular momentum (OAM) as new resource for modulation in 6G.

C. OUR SURVEY

The work presented in [2], [4], [9], [10], [13], [16], [26]–[29] focused on key enabling technologies, requirements, and use cases of 6G. By contrast, we are the first to discuss state-of-the-art advances and taxonomy for 6G wireless systems to the best of our knowledge, as given in Table 2. We also present novel open research challenges and future research directions.

Our contributions are as follows:

- We explore and discuss state-of-the-art advances made toward enabling 6G systems.
- We devise a taxonomy of 6G wireless systems based on key enablers, use cases, emerging machine learning schemes, communication technologies, networking technologies, and computing technologies.
- We discuss several open research challenges and their possible solutions.
- We provide an outlook for future research.

The rest of our survey is organized as follows. Section II presents state-of-the-art advances toward enabling 6G systems. Moreover, a summary of features and merits with critical discussions is provided. Section III presents the devised taxonomy using key enablers, use cases, emerging machine learning schemes, communication technologies, networking technologies, and computing technologies as parameters. Open research challenges with guidelines are presented in Section IV. Section V presents potential future research directions and finally, paper is concluded in Section VI.

II. 6G:STATE-OF-THE-ART

This section presents state-of-the-art advances that enable 6G, as summarized in Table 3.

Khan *et al.* reviewed federated learning at the network edge [30]. Resource optimization and incentive mechanism design for federated learning at the network edge was considered. First, key design aspects for enabling federated learning at the network edge were presented. These key design aspects are resource optimization, incentive mechanism design, learning algorithm design, and hardware–software co-design. Second, a Stackelberg-game-based incentive mechanism was proposed. Additionally, a few numerical results were presented to validate their Stackelberg-game-based incentive mechanism. Finally, several open research challenges and future research directions were presented. Although the Stackelberg game-based incentive mechanism provides reasonable results, it is recommended to further propose contract theory-based incentive mechanism.

Wang *et al.* proposed a framework; namely, In-Edge AI, to enable intelligent edge computing and caching via machine learning [31]. Deep Q-learning agents are placed at the edge nodes in the proposed framework to offer intelligence. An improved version of deep Q-learning; namely, double deep Q-learning network (DDQN), was used in the paper for two cases of edge caching and computational offloading. Centralized DDQN and federated learning-based DDQN were proposed to train the DDQN. Although federated-learning-based DDQN has a generally slightly degraded performance than centralized DDQN, it offers a substantially lower consumption of communication resources for training the learning agent at the network edge. The In-Edge AI framework showed promising results for caching and edge computing, there is a need to propose an incentive mechanism and business model for the proposed framework. The In-Edge AI framework has a large number of mobile users, service providers, and different operators. Therefore, enabling their successful interaction requires effective incentive mechanism design. Stackelberg game and contract theory-based incentive mechanisms can be proposed for successful interaction between a variety of players.

Mozaffari *et al.* introduced the concept of 3D cellular networks mainly based on drones [33]. They integrated cellular-connected drone users with drone base stations considering the two problems of 3D cell association and network planning. They introduced a new scheme using truncated octahedron cells to compute the minimum number of drone base stations and their feasible locations in a 3D space. They also derived an analytical expression for frequency planning. Finally, they presented an optimal-latency-aware 3D cell association scheme. Mumtaz *et al.* provided an overview of challenges and opportunities for terahertz communication in vehicular networks [34]. They discussed different available bands in the terahertz communication range. The authors discussed different standardization activities regarding terahertz communication. However, 6G is currently in initial phases and significant efforts are needed to turn its vision of 6G using terahertz band into reality. There is a need to define novel standards for 6G to incorporate terahertz communication in addition to other emerging communication and computing technologies. Nawaz *et al.* presented the vision of quantum machine learning for 6G [32]. The authors reviewed state-of-the-art machine learning techniques intended for use in next-generation communication networks. Moreover, they discussed state-of-the-art quantum communication schemes and few open research challenges, and proposed a quantum-computing-assisted machine learning framework for 6G networks. Finally, they discussed open research issues related to the implementation of quantum machine learning in 6G.

Salem *et al.* considered the nanosensor network using blood as a medium for terahertz communication to enable smart healthcare applications [35]. They proposed an electromagnetic model for blood using effective medium theory. An advantage of the proposed model is the flexibility of specifying red blood cell volume fraction and particle shape. Another advantage of their work is finding the relation of molecular noise and path loss with the concentration of red blood cells. Molecular noise and path loss decrease with an increase in concentration of red blood cells, and vice versa. Finally, the authors concluded that the particle shape of red blood cells has no effect on blood, although it is considered a medium for terahertz communication.

Canovas-Carrasco *et al.* [36] proposed an architecture using terahertz communication for hierarchical body area nanonetworks. They conceptually designed two kinds of devices for the proposed architecture; namely, nanonodes and nanorouters. They proposed a novel communication scheme to enable communication between nanonodes using the terahertz band. They carried out communications using the human hand and mitigated molecular absorption noise and path loss. Another advantage of the proposed architecture is coping with the issue of the decrease in transmission rate due to energy limitations. They proposed using energy harvesting from the blood stream and external sources to improve transmission rate. Although the proposed architecture for body area nanonetworks offers significant advantages and mainly considered communication between nano-router and nanonodes, it is preferable to analyze the communication model between the external devices and body area nanonetworks to enable dispatching of sensor data to end-users.

III. TAXONOMY

We consider key enablers, emerging machine learning schemes, communication technologies, networking technologies, and computing technologies, to devise the taxonomy, as shown in Fig. 3. Further discussion is provided in the following subsections.

TABLE 3. Summary of state-of-the-art.

Reference	Category	Feature	Merit
Khan *et al.* [30]	Edge AI	• Resource optimization in federated learning at network edge is considered • Incentive mechanism based on Stackelberg game is proposed	• Key design aspects of federated learning are presented. • Novel open research challenges with possible solutions are presented. • Few recommendations for future research are presented.
Wang *et al.* [31]	Edge AI	• Intelligent edge caching and computation offloading are considered. • An In-Edge AI framework is proposed	• Double deep Q-learning networks are used for better performance • DDQN with federated learning is used to reduce the transmission overhead during the training process.
Nawaz *et al.* [32]	Quantum machine learning	• Reviewed quantum machine learning for 6G wireless networks • Proposed a framework for quantum machine learning in 6G wireless networks	• Presented the key research challenges for implementation of quantum machine learning in 6G wireless networks
Mozaffari *et al.* [33]	3D networking	• 3D cellular networks are introduced • 3D networking planning and association are proposed.	• Proposed a latency-minimal scheme for association between the drone base station and drone user. • For feasible integer frequency reuse factors in 3D networks, an analytical expression is derived. • The proposed 3D association scheme results in significant latency minimization to serve the drone users compared to traditional cellular association schemes.
Mumtaz *et al.* [34]	Terahertz communication	• Terahertz communication for vehicular networks is considered • Provided bandwidth analysis of available bands for terahertz communication.	• Challenges and opportunities for terahertz communication for next generation vehicular communication networks are presented.
Salem *et al.* [35]	Terahertz communication	• Considered nano-sensor networks using terahertz communication for health-care applications. • Presented an electromagnetic model based on effective medium theory for blood.	• The proposed model offers flexibility of specifying red blood cells volume fraction and particle shape. • The authors found that both molecular noise and path loss decreases with an increase in concentration of red blood cells and vice versa.
Carrasco *et al.*[36]	Terahertz communication	• Proposed an architecture for hierarchical body area nano-networks. • Two types of nano devices, such as nano-router and nano-nodes are conceptually designed for the proposed architecture using available electronic components.	• They proposed a scheme for communication between nano devices using terahertz band. • The impact of molecular absorption noise and path loss on electromagnetic waves propagation is mitigated. • Energy management has been performed for low-energy nano devices.

A. KEY ENABLERS

A 6G system will use a wide variety of computing, communication, networking, and sensing technologies to offer different novel smart applications. The key enablers of 6G wireless systems are edge intelligence, homomorphic encryption, blockchain, network slicing, AI, photonics-based cognitive radio, and space-air-ground-integrated network. Although network slicing was proposed in 5G as a key enabling networking technology, its true realization is expected in 6G. Network slicing based on software-defined networking (SDN) and network function virtualization (NFV) employs shared physical resources to enable slices of different applications. The process of network slicing involves the optimization of a variety of network parameters. One way is to model them using mathematical optimization problem that can be solved using different schemes, such

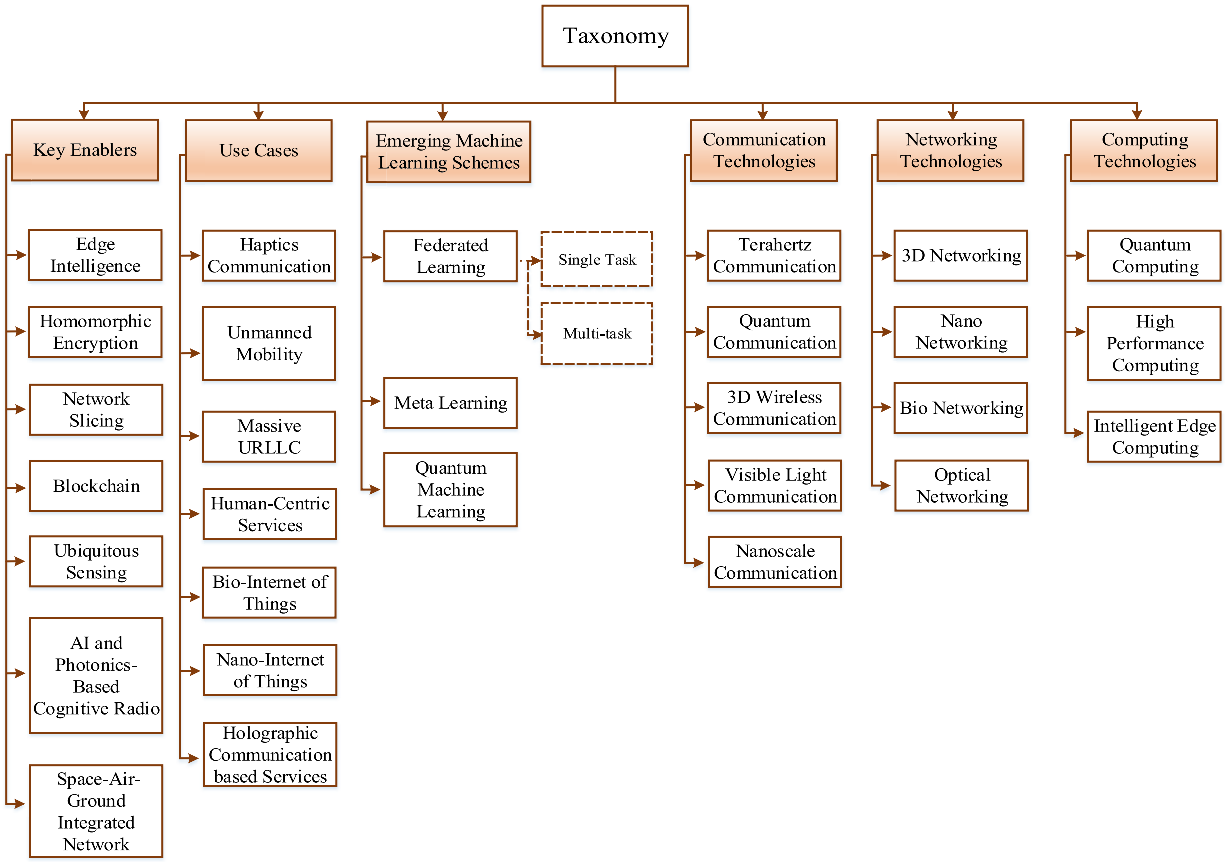

FIGURE 3. Taxonomy of 6G wireless systems.

as convex optimization schemes, game theory, and iterative schemes. However, mostly the later schemes are highly complex. Therefore, there is a need to propose new solutions (e.g., machine learning-based solutions) with low complexity. Over 2, 000 configurable parameters are expected in a typical 6G smart device [31]. Therefore, using smart devices based on effective machine learning schemes is indispensable. Photonics-based cognitive radio assisted by machine learning will enable intelligence in 6G radio and offer features of scalability, ultra-reliability, low latency, and ultra-broadband features.

Blockchain is a distributed ledger that will enable secure, robust exchange of data among smart citizens [37]–[39]. Therefore, it can be considered one of the key technologies for 6G to enable smart supply chain, smart grid, and smart healthcare [40]–[42]. Although blockchain will be considered to be one of the key enabling technologies of 6G systems, it has few challenges. Mainly, these challenges are simultaneous scalability and reliability, high-latency, and high energy consumption for running consensus algorithm [43], [44]. 6G systems are envisioned mainly to enable extremely low latency (i.e., less than 1ms), low energy consumption (i.e., 1pJ/b), and reliability (i.e., $1 - 10^{-9}$). Therefore, significant efforts for designing blockchain with low-latency, ultra-high scalability and reliability, are required to truly enable its existence into 6G. On the other hand, ubiquitous sensing involves machine vision and 3D-range imaging using video-captured information to enable sensing automation and smart decision making [45], [46]. Ubiquitous sensing will serve as a key technology of smart cyber–physical systems for enabling novel 6G applications [47]. Space-air-ground integrated network (SAGIN) consists of terrestrial communication networks, aerial networks, and satellite networks, which can be considered to one of the key enablers of 6G [2]. One of the many advantages of SAGIN is to provide coverage to scarce infrastructure areas by drones-based BSs. Other advantages of SAGIN are strong resilience, high throughput, and large coverage [48]. Although SAGIN offers several benefits, it suffers from the challenge of how to effectively perform end-to-end quality of service management, mobility management, load balancing, power control, and spectrum allocation, among all network segments. Therefore, we must design novel schemes for SAGIN-enabled 6G to enable optimal end-to-end performance among all the network segments.

B. USE CASES

Although 5G wireless networks were conceived to provide a wide variety of smart services, several services disrupt the vision of 5G design. Generally, 5G use cases have three main classes, such as URLLC, enhanced mobile broadband (eMBB), and massive machine-type communication (mMTC). However, several new applications are disrupting the vision of 5G use cases and we need new use cases. For instance, consider XR (i.e., combining mixed reality, augmented reality, and virtual reality [49]) and brain-computer interaction that requires 5G-eMBB high data rates, low-latency, and high reliability. Therefore, we must define new use cases for these emerging applications. The novel 6G services are haptics, autonomous connected vehicles, massive URLLC (mURLLC), human-centric services, bioInternet of things (B-IoT), nanoInternet of things (N-IoT), and mobile broadband reliable, low-latency communication [2], [9], [28]. Novel 6G use cases are provided below:

- **Massive URLLC:** mURLLC denotes IoE applications based on application-dependent scaling of classical URLLC [2]. mURLLC will be based on merging massive machine-type communication and 5G URLLC. This use case will offer a trade-off between reliability, scalability, and latency. Examples of mURLLC are smart factories and smart grids, which require ultra-reliability and low-latency communication. In addition, we expect a massive number (more than $10^6/km^2$) of nodes for cyber-physical system-enabled smart factories and smart grids in the future [10]. Therefore, we must scale the classical 5G URLLC to a massive URLLC to meet the requirements of these new applications.
- **Human-centric services:** Although 5G offers numerous advantages, such as basic augmented and virtual reality services, high-definition video streaming, internet protocol television, among others, there is a need to propose services that are more human-centric. In contrast to 5G use cases, the human-centric services use case represents a service that is intended to fulfill new user-centric metrics (i.e., quality of physical experience) [2], [50]. A common example is brain–computer interface whose performance can be measured via human physiology.
- **Haptics communication:** Haptic communication, a form of non-verbal communication, deals with enabling sense of touch from a remote place [51]. However, enabling this type of real-time interactive experience using 6G requires substantial design efforts.
- **Holographic communication based services:** This use case is based on a remote connection with an ultra-high accuracy [9]. Holographic communication will be based on multiple-view camera image communication that requires substantially higher data rates (Tbps) [14].
- **Unmanned Mobility:** This use case deals with fully autonomous connected vehicles that offer complete unmanned mobility, safe driving, smart infotainment, and enhanced traffic management [9].
- **Nano-Internet of Things:** N-IoT uses nanodevices for communication over a network. For instance, nanocommunication in a smart factory can be used to monitor carbon emissions, water quality, gaseous fumes, and humidity. As N-IoT mainly uses molecular communication which seems difficult to enable by 5G. We should consider 6G for molecular communication-based N-IoT [52]. Nano-networks use terahertz band for better performance [10], which falls in 6G [2]. Therefore, we can say that N-IoT can be better enabled by 6G. The key requirements for N-IoT must be specified based on 6G because N-IoT is in its infancy. The N-IoT has several implementation challenges, such as physical layer schemes for macro and micro-scale molecular communication (i.e., detection and channel estimation), standardization of layered architecture, design of nano-things, and development of application-oriented testbeds.
- **Bio-Intenet of Things:** B-IoT is based on the communication of biodevices (nanobiological devices) using IoT. This use case represents the variety of smart healthcare applications using biocommunication. Similar to N-IoT, the key performance requirements for B-IoT must be specified. The works in [35] and [36] used the terahertz band, which is one of the key enablers of 6G. Therefore, we can say that B-IoT can be effectively enabled by 6G.

C. EMERGING MACHINE LEARNING SCHEMES

Machine learning (ML) is considered one of the key drivers of 6G. ML recently elicited great attention in enabling numerous smart applications. In 6G, ML is expected to not only enable smart applications but also provide intelligent medium access control schemes and intelligent transceivers [29], [53], [54].Thus, ML can be one of the fundamental pillars of the 6G wireless network. Generally, we can divide ML into several types: traditional machine learning, federated learning, meta learning, and quantum machine learning. Traditional machine learning is based on the migration of data from end devices to a centralized server for training the machine learning model. However, this approach suffers from issues of privacy concerns and high overhead in the migration of data to a centralized server [55]. Furthermore, centralized machine learning generally suffers from high power consumption during the training process for large datasets. Coping with this issue, one can use distributed machine learning. Distributed machine learning can lead to high-performance computing by enabling parallel computation of machine learning models at distributed locations [56]. There can be two possible ways, such as the data-parallel approach and model-parallel approach, to distribute the machine learning tasks. The data-parallel approach is based on a division of data among nodes, with all nodes running the same machine learning model. On the other hand, the model-parallel approach is based on training portions of the machine learning model which are distributed across many nodes, with every node having an exact copy of the data. However, this approach might not be feasible for many machine learning models that cannot be split up into parts.

To deploy distributed machine learning models using data-parallel approach, there can be many possible ways. These ways include centralized, tree-based decentralized, parameter server-based decentralized, and fully distributed [56].

In a centralized ensemble-based distributed learning, a strict aggregation fashion at one central location is adopted. Tree-based decentralized learning allows intermediate aggregation at child nodes before a central aggregation takes place [57]. Parameter server-based decentralized learning is based on storing all the client's updates on a shared parameter server. In case of fully distributed, all nodes directly communicate with each other for the model sharing. On the other hand, federated learning can be considered as a special type of distributed machine learning. Federated learning was recently adopted for edge networks to tackle these prominent challenges of traditional machine learning [30], [31]. Federated learning enables machine learning in a distributed manner by enabling on-device machine learning without migrating data from end devices to the edge/cloud server. However, federated learning has its inherent challenges including communication and computation resource optimization, incentive mechanism design, and local device learning algorithm design. Quantum machine learning combines quantum physics and machine learning to enable fast training of machine learning models. Meta learning enables the machine learning models to learn, but has complexity in design because various machine learning models have different natures.

D. COMMUNICATION TECHNOLOGIES

A 6G system will use novel communication technologies to enable various smart applications. These communication technologies are terahertz communication, quantum communication, 3D wireless communication, visible light communication, nanoscale communication, and holographic communication. Recently, 3GPP has developed a new radio access technology; namely, 5G new radio using sub-6 GHz and mmWave bands for enabling high data rates [58]. To enable further higher data rates, 6G will use terahertz bands in addition to mmWave bands. Generally, terahertz communication uses frequencies from 0.1 to 10 terahertz and is characterized by short-range, medium-power consumption, high security, and robustness to weather conditions [59]–[61]. Terahertz communication offers several advantages, but several challenges must be resolved to enable its use in 6G. These challenges involve the design of efficient transceivers with advanced adaptive array technologies to increase its range. Another important aspect of 6G is the use of 3D communication which involves the integration of ground and airborne networks. Unarmed aerial vehicles and low-orbit satellites can be used as base stations for 3D communication [62]. In contrast to 2D (ground) communication, 3D communication has a substantially different nature because of the introduction of altitude dimension. Therefore, novel schemes are necessary for resource allocation and mobility handling for 3D communication networks. Nanoscale communication is a new communication technology that uses an extremely short wavelength for communication and is suitable for a distance of 1 m or cm. Key challenges of nanoscale communication are nanoscale transceiver design and channel modeling.

Visible light communication can be used to enable several 6G applications using a visible light spectrum that ranges from 430 THz to 790 THz [63], [64]. The main advantage of visible light communication is the use of illumination sources for lighting and communication. Moreover, visible light communication offers a substantial large bandwidth and interference-free communication from radio frequency waves. However, visible light communication with low-range, novel transceivers (acting as illumination source and communication source) must be designed to enable different visible light communication-based applications. Furthermore, several other challenges must be resolved to enable 6G with visible light communication. Such challenges include connectivity of light-emitting diode to the Internet, inter-cell interference, mobility and coverage, among others [63]. To enable 6G with a high capacity, one can deploy light-emitting diodes for visible light communication in a dense fashion. However, it will suffer from inter-cell interference which must be given proper attention. To enable seamless connectivity to users using visible light communication, it is essential to the handle mobility problem. In a typical visible light communication cell, there exists significant variations in signal-to-interference-ratio. Therefore, we must effectively handle the mobility issues using visible light communication. Quantum communication has the inherent feature of high security, which makes it preferred for 6G [65], [66]. The simultaneous achievement of long-distance and high rates is contradictory in quantum communication [67]. Therefore, repeaters must be used to enable secure long-distance, high-data-rate quantum communication. However, current repeaters cannot be used for quantum communication, and new repeaters must be designed.

E. NETWORKING TECHNOLOGIES

Novel networking technologies for 6G are nanonetworking, bionetworking, optical networking, and 3D networking [68]. The operation of the N-IoT is based on molecular communication. Different materials, such as graphene and meta materials can be used to build nanometer-range devices. B-IoT using biological cells are used for communication using IoT [69], [70]. B-IoT and N-IoT are seemingly integral parts of future 6G smart services but have several implementation challenges. The design of physical layer technologies for molecular communication is a challenging task. Apart from physical layer techniques, novel routing schemes must be proposed because of the substantially different nature of B-IoT and N-IoT compared with traditional IoT. Efficient nanodevices and biodevices must be developed for N-IoT and B-IoT because they are in infancy. However, 3D networking uses drone-based user devices and drone-based base stations to enable communication networks. Thus, novel models must be devised for a 3D communication network due to its substantially different nature compared with a 2D network.

F. COMPUTING TECHNOLOGIES

A 6G system involves a wide variety of sources of different smart applications that generate an enormous amount of data. High-performance computing and quantum computing must be used to enable intelligent data analytics. Quantum computing is expected to revolutionize the field of computing by enabling higher speeds that users have never experienced until now [71], [72]. The key feature of quantum communication is secure channels, where every channel carries its distinct security protocols constructed into encrypted data. These features of security in addition to ultra-high speed make quantum computing preferable for secure 6G smart applications. Other than quantum computing, intelligent edge computing is required for 6G to provide intelligent on-demand computing and on-demand storage capabilities with extremely low latency to end nodes [73]–[77].

IV. OPEN RESEARCH CHALLENGES

We present several novel open research challenges for 6G. Their causes and possible solutions are discussed and summarized in Table 4.

A. AI-BASED ADAPTIVE TRANSCEIVERS

How do we enable a 6G transceiver with a large number of intelligent, adaptive tunable parameters? A typical 6G transceiver is expected to have numerous tunable parameters. These parameters can be adaptively tuned via machine learning algorithms. For instance, consider the training of a deep Q-learning agent for intelligent caching in XR applications. The Q-learning agent can be trained in two ways: traditional machine learning and federated learning. Traditional machine learning requires shifting of data from end devices to the edge/cloud server for the training of the deep Q-learning agent deployed at the edge/cloud server. The sending of data from end devices to the edge server has a substantial cost in terms of wireless communication resources. By contrast, federated learning can be used to train the deep Q-learning agent efficiently by reducing wireless resource usage through sending only model updates (that have much less size compared with the whole training data) to the edge/cloud server. Similarly, federated learning can be used to enable intelligence in an adaptive transceiver.

B. INTELLIGENT WIRELESS ENERGY HARVESTING

How do we enable 6G smart applications in a sustainable fashion? Enabling 6G applications sustainably requires the use of energy-efficient devices and renewable energy sources. Wireless energy harvesting can be one of possible ways to enable sustainable operation of 6G. Wireless energy harvesting covers numerous harvesting scenarios: dedicated radio frequency harvesting sources, interference-aware harvesting, and ambient sunlight harvesting. However, substantial variations exist in harvested energy for these wireless energy-harvesting sources. Therefore, an intelligent power control must be developed for energy-harvesting devices. Traditional power control schemes for energy-harvesting devices assume the known system state (incoming harvesting energy and wireless channel), but this information is not available practically. Machine learning can be used to predict the future system state and address these challenges. Reinforcement learning can be one of the possible solutions with unknown statistical knowledge and observable current system state, but it has a limitation of use in only finite system states. Another approach to cope with this limitation is the use of Lyapunov opportunistic optimization and online-learning-based schemes [78].

C. DECENTRALIZED AND SECURE BUSINESS MODELS

How do we enable a wide variety of geographically distributed and diverse players in 6G to interact cost effectively and securely? Novel decentralized, secure business models must be designed to enable a cost-effective interaction among various geographically distributed players in 6G economically and securely. A centralized business model will offer high latency, which is undesirable for ultra-high-speed 6G smart services. Therefore, new distributed business models for 6G must be developed. Different schemes can be used for security in business models. One of these schemes can be a blockchain-based secure service brokering between suppliers and providers.

D. INTELLIGENT CELL-LESS ARCHITECTURE

How do we enable intelligent management of a large variety of different communication technologies in the cell-less architecture of 6G wireless systems? A 6G system will be based on a true cell-less architecture to avoid handover issues and offer seamless communication with improved quality of experience to end users. Therefore, a novel architecture for 6G enables a seamless interaction between numerous communication technologies, such as visible light communication, millimeter-wave communication, and terahertz communication. All access points/base stations of different communication techniques should serve the users in collaboration to improve the signal-to-noise-plus-interference ratio. Intelligent operation of 6G can be enabled via intelligent cognitive radio with self-sustaining, adaptive features. A software-defined cognitive radio using machine learning can be used to perform several intelligent operations: self-protection against interference, self-fault recovery, self-optimization, and self-management. One possible way to enable software-defined cognitive radio is the use of deep Q-learning. Quantum machine learning can also be used to enable fast learning of machine learning models [32].

E. DISTRIBUTED SECURITY MODELS

How do we enable distributed machine learning and distributed computing for 6G while preserving user privacy? A 6G wireless system will use AI to enable different smart applications and networking functions. Traditional machine learning models migrate user data to the edge/cloud server for training the learning model. Therefore, homomorphic

TABLE 4. Summary of the research challenges and their guidelines.

Challenges	Causes	Guidelines
AI-based adaptive transceivers	• Large variety of tunable parameters • Significant variations in physical layers requirements for different applications	• Deep Q-learning based intelligent transceiver • Federated learning based transceiver
Distributed and secure business models	• Strict-latency 6G applications • Geographically distributed services providers over a large area	• Novel distributed business models • Blockchain based secure service brokering
Intelligent wireless energy harvesting	• Sustainable operation • Existence of a wide variety of interference signals	• Reinforcement learning-based energy harvesting schemes • Lyapunov optimization and online learning based schemes
Intelligent cell-Less architecture	• Management of several communication technologies with different features • Different communication bands with distinct features	• Deep Q-learning-based cognitive radio • Quantum machine learning based software-defined cognitive radio
Distributed security models	• Training of machine learning models at the network edge • Requirement of distributed authentication with low-latency for smart applications	• Homomorphic encryption • Distributed-ledger based authentication schemes
Reconfigurable smart reflecting surfaces-enabled 6G	• High path loss for millimeter wave and terahertz communication. • Loss in capacity.	• Deep learning-based reconfigurable smart reflecting surface • Reconfigurable smart reflecting surface as an access point

encryption, which enables sending of encrypted data to the edge/cloud server rather than un-encrypted data, can be used to address this type of privacy concern. A novel distributed authentication scheme must be proposed for 6G wireless systems. Distributed ledger technology (using blockchain)-based authentication schemes can be one of the possible solutions for 6G-distributed authentication.

F. RECONFIGURABLE SMART REFLECTING SURFACES-ENABLED 6G

How do we enable 6G wireless systems with reconfigurable smart reflecting surfaces to simultaneously improve throughput and energy efficiency? To enable 6G with high capacity using millimeter-wave and terahertz communication, we can use massive multiple-input-multiple-output (MIMO) with antenna arrays for meeting increasing demands in capacity [79]. Although an increase in frequency reduces the scattering and diffraction effect, it suffers from the blocking of electromagnetic waves by buildings. Additionally, high-frequency communication suffers from significant path loss. Coping with the aforementioned issues, we can use reconfigurable smart reflecting surfaces. A typical reconfigurable smart reflecting surface is comprised of several reconfigurable reflecting elements that can reflect impinging electromagnetic waves. In [80], Liaskos *et al.* used deep learning-based reconfigurable smart surface to improve wireless communication performance. Another approach is to use reconfigurable smart reflecting surface-based access points [81], which involve sending of an unmodulated carrier signal to smart surfaces with negligible fading by radio frequency signal generator. The reconfigurable smart reflecting surface then uses phase shifts to convey the bits.

V. POTENTIAL FUTURE DIRECTIONS

We derive several future research directions (overview is presented in Fig. 4) from the study as follows.

A. ADAPTIVE MACHINE LEARNING-ENABLED 6G

Machine learning can be considered an integral part of 6G, but applying a specific type of machine learning technique for 6G must examine the application nature. For instance, consider autonomous driving cars that generate $4,000$ gigaoctet of data every day [82]. In this scenario, real-time interaction is necessary. Centralized machine learning based on one-time training can be used. However, the model trained via centralized machine learning might not produce good results

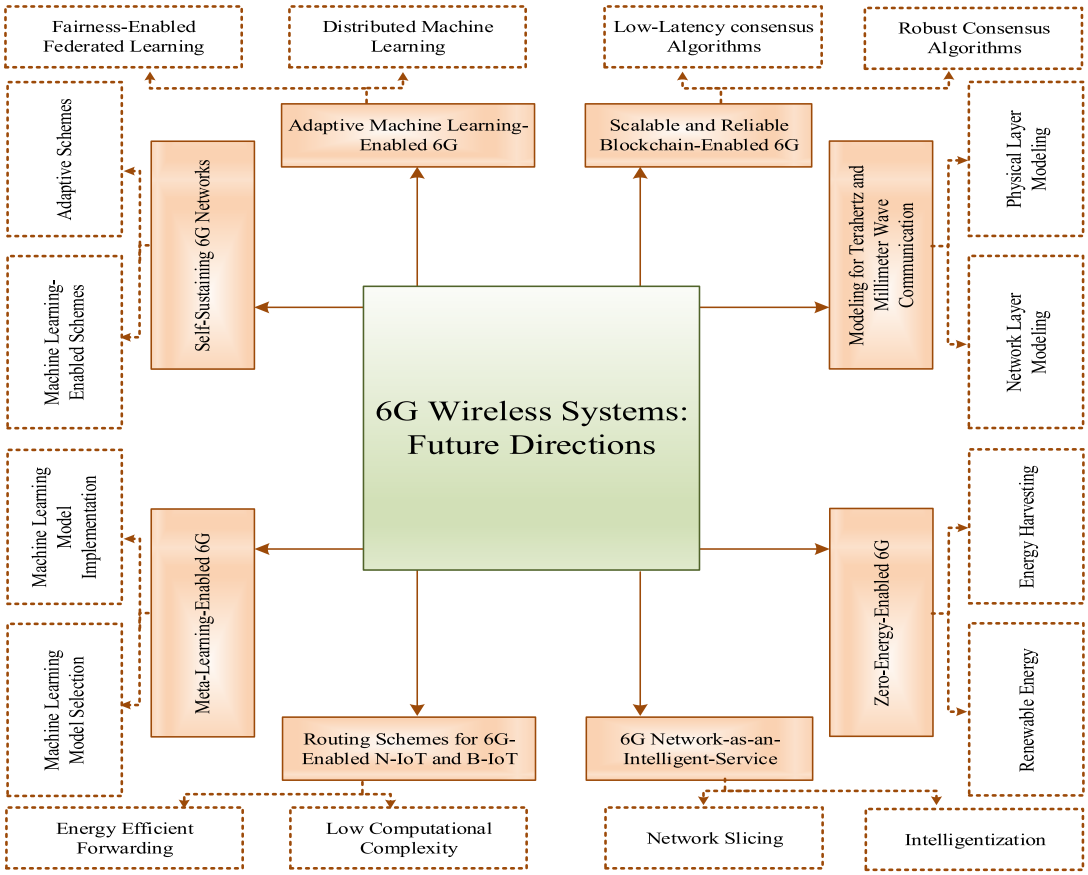

FIGURE 4. 6G wireless systems: future directions.

due to the frequent addition of new data. Therefore, federated learning is preferred over centralized machine learning for this type of scenario. Federated learning offers the advantage of considering newly added data training but suffers from fairness issues. q-fair federated learning was proposed to deal with fairness issues [83]. In q-federated learning, local learning weights of devices with poor performance are given more weight, and vice versa. Although q-fair federated learning can enable efficient federated learning via adjusting weights, it suffers from the challenge of how to dynamically adjust weights. Therefore, centralized machine learning, where user privacy has less importance and does not suffer from frequent addition of data, can be used.

Another way is to use distributed learning based on training a machine learning model using a dataset at a centralized location. Machine learning model parameters are then sent to the end devices. Finally, the end devices update the global learning models using their local datasets. The advantage of distributed machine learning is the one time-sharing of learning model parameters between the centralized server and end devices, thus avoiding resource fairness challenges. However, distributed learning needs the dataset at the centralized location having sufficient data (might not be all device data) from training, which again causes some privacy leakage to a lesser extent than centralized machine learning.

B. SCALABLE AND RELIABLE BLOCKCHAIN-ENABLED 6G

Blockchain is a promising technology that offers secure storage of transactions in a distributed, immutable ledger. Various smart services that can be enabled by blockchain are smart healthcare, smart supply chain management, smart transportation, and smart property management. A 6G system is intended to provide enhanced scalability and reliability, extremely low latency, and low energy consumption. However, existing blockchain consensus algorithms might pose limitations in terms of scalability, reliability, latency, and energy consumption [84]. Implementation of blockchain to achieve key design aspects, such as fault tolerance, security, low latency, and decentralization simultaneously poses substantial challenges on scalability and reliability, which is one of the primary goals of 6G systems [2], [85]. A novel consensus algorithm that offers enhanced reliability and scalability while providing tradeoffs between fault tolerance, security, and latency must be proposed to benefit from the deployment of blockchain in 6G systems.

C. 6G NETWORK-AS-AN-INTELLIGENT-SERVICE

A 5G network was envisioned to enable numerous smart services via transformation of network-as-an-infrastructure to network-as-a-service. Network-as-a-service offers the use of shared physical resources via network slicing to serve different smart services [86]. Network slicing uses SDN and NFV as key enablers. SDN offers separation of the control plane from the data plane, thus offering efficient network management [87]. NFV allows the cost-efficient implementation of different networking functions on generic hardware using virtual machines. Although network slicing enables efficient resources usage while fulfilling end-user demands, it might not perform well with an increase in network heterogeneity and complexity [4].Therefore, network-as-a-service must be transformed to network-as-an-intelligent-service. Network intelligentization will enable 6G systems to adjust various parameters adaptively, thus offering enhanced performance.

D. SELF-SUSTAINING 6G NETWORKS

A self-organizing (i.e., self-operating) network offers optimization, management, configuration, and planning in an efficient, fast manner [88], [89]. Self-organizing network was systematically outlined in 3GPP Release 8. However, the traditional self-organizing networking scheme might not be feasible for 6G systems due to the presence of a complex, dynamic environment. Therefore, a novel, self-sustaining 6G network architecture must be proposed [2]. Self-sustaining 6G systems must adapt to the highly dynamic environment sustainably. Furthermore, emerging machine learning schemes must be used to enable efficient, self-sustainable 6G systems.

E. MODELING FOR TERAHERTZ AND MILLIMETER WAVE COMMUNICATION

We propose novel models (physical layer and networking layer) for millimeter-wave and terahertz bands because of their substantially different nature compared with existing lower-frequency bands. For fixed nodes, terahertz communication has fewer challenges than mobile nodes [90]. Therefore, we must propose novel schemes for terahertz communication in case of mobile nodes. Based on the new design models, we can propose an optimization framework to enable 6G services according to their key performance indicators.

F. ZERO-ENERGY-ENABLED 6G

We recommend designing zero-energy 6G systems. A 6G wireless communication system must use renewable energy and radio-frequency-harvesting energy for its operation (i.e., hybrid energy sources). However, energy from the grid station must be used when radio frequency harvesting energy level fall below the required energy level for their operation. The zero-energy wireless system must return the equivalent amount of energy to the grid during the time of excess radio frequency harvesting energy to account for the consumed energy from the grid.

G. ROUTING SCHEMES FOR 6G-ENABLED N-IoT AND B-IoT

N-IoT and B-IoT have a substantially different nature compared with traditional IoT. Therefore, novel routing schemes must be developed. Routing schemes with low computational complexity and short-range communication must be proposed due to limited energy, short-range communication, and low computing capabilities of nanonodes and bionodes. Moreover, nanonetworks can operate in a terahertz band, thus requiring substantial effort for routing protocol design [91]. Therefore, novel routing schemes based on energy-efficient forwarding and low computational complexity must be proposed for N-Iot and B-IoT.

H. META-LEARNING-ENABLED 6G

Machine learning is considered an integral part of 6G. However, training the machine learning model by selecting appropriate learning model parameters requires extensive experimentation. By contrast, meta learning provides machine learning models the capability to learn. However, 6G smart applications enabled by machine learning have a substantially different nature. Therefore, we recommend novel meta learning models to assist the learning of numerous machine learning models by offering them appropriate learning model parameters to enable different 6G smart applications. A two-stage meta learning framework can be used to solve different machine learning problems in 6G [92]. The first stage can select the machine learning model, and the second stage will implement the selected machine learning model.

VI. CONCLUSION

We have presented recent advances made toward enabling 6G wireless systems, proposed a comprehensive taxonomy based on different parameters, and presented several open challenges along with important guidelines. We conclude that 6G systems will unlock the full potential of smart cities via enabling Internet of everything based smart services. AI will be an integral part of the 6G wireless system to solve complex network optimization problems. Terahertz communication will be considered as one of the key communication bands for 6G systems. It is essential to propose novel models for terahertz communication. Furthermore, new models must be proposed for quantum communication that is currently in infancy.

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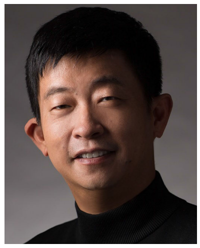
LATIF U. KHAN received the M.S. degree (Hons.) in electrical engineering from the University of Engineering and Technology (UET), Peshawar, Pakistan, in 2017. He is currently pursuing the Ph.D. degree in computer engineering with Kyung Hee University (KHU), South Korea. Prior to joining KHU, he was a Faculty Member and a Research Associate with UET. He is working as a Leading Researcher at the Intelligent Networking Laboratory under a project jointly funded by the prestigious Brain Korea 21st Century Plus and Ministry of Science and ICT, South Korea. He has published his works in highly reputable conferences and journals. His research interests include analytical techniques of optimization and game theory to edge computing and end-to-end network slicing. He received the Best Paper Award in the 15th IEEE International Conference on Advanced Communications Technology, Pyeongchang, South Korea, in 2013.

IBRAR YAQOOB (Senior Member, IEEE) received the Ph.D. degree in computer science from the University of Malaya, Malaysia, in 2017. He worked as a Researcher and a Developer at the Centre for Mobile Cloud Computing Research (C4MCCR), University of Malaya. He is currently a Research Professor with the Department of Computer Science and Engineering, Kyung Hee University, South Korea, where he completed his Postdoctoral Fellowship under the prestigious grant of the Brain Korea 21st Century Plus. His numerous research articles are very famous and among the most downloaded in top journals. He has reviewed over 200 times for the top ISI-Indexed journals and conferences. He has been listed among top researchers by Thomson Reuters (Web of Science) based on the number of citations earned in last three years in six categories of computer science. He has been involved in a number of conferences and workshops in various capacities. His research interests include big data, edge computing, mobile cloud computing, the Internet of Things, and computer networks. He is serving/served as a Guest/Associate Editor in various journals.

MUHAMMAD IMRAN (Member, IEEE) is currently an Associate Professor with King Saud University. His research interests include MANET, WSNs, WBANs, M2M/IoT, SDN, security, and privacy. He has published a number of research papers in refereed international conferences and journals. He served as the Co-Editor-in-Chief of EAI Transactions and an Associate/Guest Editor for IEEE ACCESS, the *IEEE Communications Magazine*, the *IEEE Wireless Communications Magazine*, *Future Generation Computer Systems*, *Computer Networks*, *Sensors*, IJDSN, JIT, WCMC, AHSWN, IET WSS, IJAACS, and IJITEE.



ZHU HAN (Fellow, IEEE) received the B.S. degree in electronic engineering from Tsinghua University, in 1997, and the M.S. and Ph.D. degrees in electrical and computer engineering from the University of Maryland at College Park, College Park, in 1999 and 2003, respectively. From 2000 to 2002, he was a Research and Development Engineer with JDSU, Germantown, MD, USA. From 2003 to 2006, he was a Research Associate with the University of Maryland. From 2006 to 2008, he was an Assistant Professor with Boise State University, Idaho. He is currently a John and Rebecca Moores Professor with the Electrical and Computer Engineering Department and the Computer Science Department at the University of Houston, TX. He is also the Chair Professor with National Chiao Tung University. His research interests include wireless resource allocation and management, wireless communications and networking, game theory, big data analysis, security, and smart grid. He has been an AAAS Fellow, since 2019, and an ACM Distinguished Member, since 2019. He received the NSF Career Award, in 2010, the Fred W. Ellersick Prize of the IEEE Communication Society, in 2011, the EURASIP Best Paper Award for the *EURASIP Journal on Advances in Signal Processing*, in 2015, the IEEE Leonard G. Abraham Prize in the field of communications systems (the Best Paper Award in the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS), in 2016, and several best paper awards in the IEEE conferences. He was an IEEE Communications Society Distinguished Lecturer, from 2015 to 2018. He has been 1% Highly Cited Researcher according to the Web of Science, since 2017.

CHOONG SEON HONG (Senior Member, IEEE) received the B.S. and M.S. degrees in electronic engineering from Kyung Hee University, Seoul, South Korea, in 1983 and 1985, respectively, and the Ph.D. degree from Keio University, Minato, Japan, in 1997. In 1988, he joined Korea Telecom, where he worked on broadband networks as a Member of Technical Staff. In September 1993, he joined Keio University. He worked at the Telecommunications Network Laboratory, Korea Telecom, as a Senior Member of Technical Staff and the Director of the Networking Research Team, until August 1999. Since September 1999, he has been a Professor with the Department of Computer Science and Engineering, Kyung Hee University. His research interests include the future Internet, ad hoc networks, network management, and network security. He is currently a member of ACM, IEICE, IPSJ, KIISE, KICS, KIPS, and OSIA. He has served as the General Chair, the TPC Chair/Member, or an Organizing Committee Member of international conferences, such as NOMS, IM, APNOMS, E2EMON, CCNC, ADSN, ICPP, DIM, WISA, BcN, TINA, SAINT, and ICOIN. He is an Associate Editor of the IEEE TRANSACTIONS ON NETWORK AND SERVICE MANAGEMENT, the *International Journal of Network Management*, and the *Journal of Communications and Networks* and an Associate Technical Editor of the *IEEE Communications Magazine*.