The Roadmap to 6G: AI Empowered Wireless Networks

Khaled B. Letaief, Wei Chen, Yuanming Shi, Jun Zhang, and Ying-Jun Angela Zhang

The authors envision 6G to undergo an unprecedented transformation that will make it substantially different from the previous generations of wireless cellular systems. In particular, 6G will go beyond mobile Internet and will be required to support ubiquitous AI services from the core to the end devices of the network. Meanwhile, AI will play a critical role in designing and optimizing 6G architectures, protocols, and operations.

Abstract

The recent upsurge of diversified mobile applications, especially those supported by AI, is spurring heated discussions on the future evolution of wireless communications. While 5G is being deployed around the world, efforts from industry and academia have started to look beyond 5G and conceptualize 6G. We envision 6G to undergo an unprecedented transformation that will make it substantially different from the previous generations of wireless cellular systems. In particular, 6G will go beyond mobile Internet and will be required to support ubiquitous AI services from the core to the end devices of the network. Meanwhile, AI will play a critical role in designing and optimizing 6G architectures, protocols, and operations. In this article, we discuss potential technologies for 6G to enable mobile AI applications, as well as AI-enabled methodologies for 6G network design and optimization. Key trends in the evolution to 6G will also be discussed.

Introduction

The wireless communications industry is one of the few industry sectors that have kept a fast growing trend with creative features for a number of decades. The current 4G LTE networks have led to the thriving of mobile Internet, enabling various innovative applications, such as mobile shopping and payment, smart home/city, mobile gaming, and so on. The great success of mobile Internet has in turn been a driving force behind the evolution of wireless technologies. The upcoming 5G network will support a wide range of services, including eMBB (enhanced mobile broadband), uRLLC (ultra-reliable and low-latency communications), and mMTC (massive machine-type communications) [1, 2].

While 5G is still at an initial stage, to maintain the sustainability and competitiveness of wireless communication systems, it is time for both the industry and academia to think about what 6G will be. There are already initiatives describing the roadmap toward 6G [3] along with the emerging trends and requirements, as well as various enabling techniques and architectures.

In contrast to previous generations, 6G will be transformative and will revolutionize the wireless evolution from "connected things" to "connected intelligence" with more stringent requirements specified as follows:

- Very high data rates, up to 1 Tb/s;
- Very high energy efficiency, with the ability to support battery-free IoT devices;
- Massive low-latency control (less than 1 msec end-to-end latency);
- Very broad frequency bands (e.g., 73GHz-140GHz and 1THz-3THz [4]);
- Ubiquitous always-on broadband global network coverage by integrating terrestrial wireless with satellite systems;
- Connected intelligence with machine learning capability.

6G will also require the support of three new service types beyond the eMBB, uRLLC, and mMTC services, as described below.

Computation Oriented Communications (COC): New smart devices call for distributed computation to enable the key functionalities, such as federated learning [5]. Instead of targeting classical quality of service (QoS) provisioning, CoC will flexibly choose an operating point in the rate-latency-reliability space depending on the availability of various communications resources to achieve a certain computational accuracy.

Contextually Agile eMBB Communications (CAeC): The provision of 6G eMBB services is expected to be more agile and adaptive to the network context, including the communication network context such as link congestion and network topology; the physical environment context such as surrounding location and mobility; and the social network context such as social neighborhood and sentiments.

Event Defined uRLLC (EDuRLLC): In contrast to the 5G uRLLC application scenario where redundant resources are in place to offset many uncertainties, 6G will need to support uRLLC in extreme or emergency events with spatially and temporally changing device densities, traffic patterns, and spectrum and infrastructure availability.

The above service types represent emerging driving applications of 6G. They can hardly be offered by 5G, not only because of their stringent requirements for higher data rates, lower latency, denser connection, and so on, but also due to their extreme demand for new performance metrics that have never been considered in 5G, for example, delay jitter, context awareness, UAV/satellite compatibility, and so on. Inspired by

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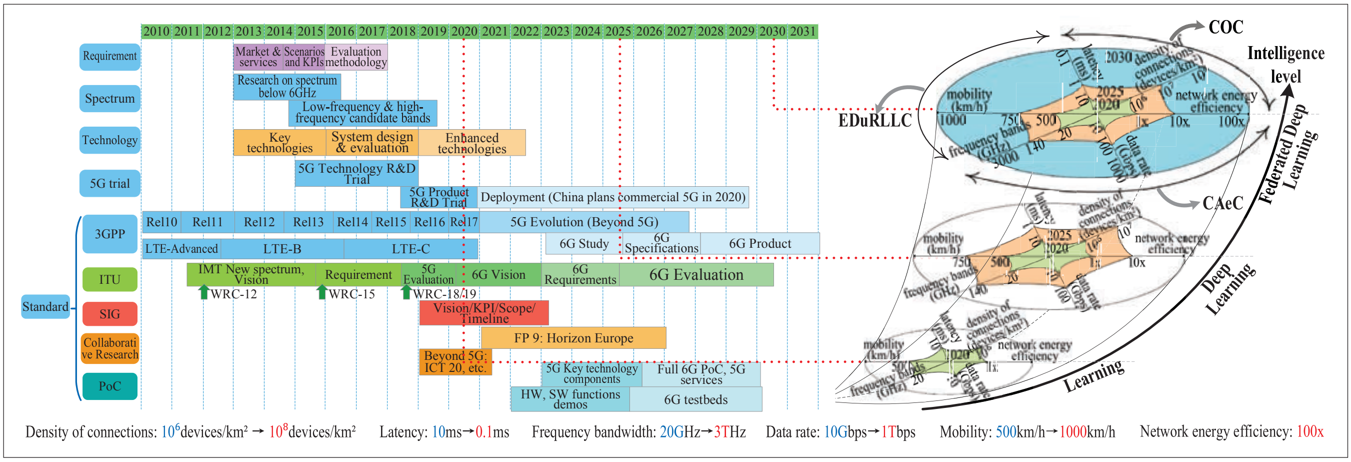

Figure 1. The roadmap of 6G. Explicit performance comparisons between 5G and 6G requirements are listed.

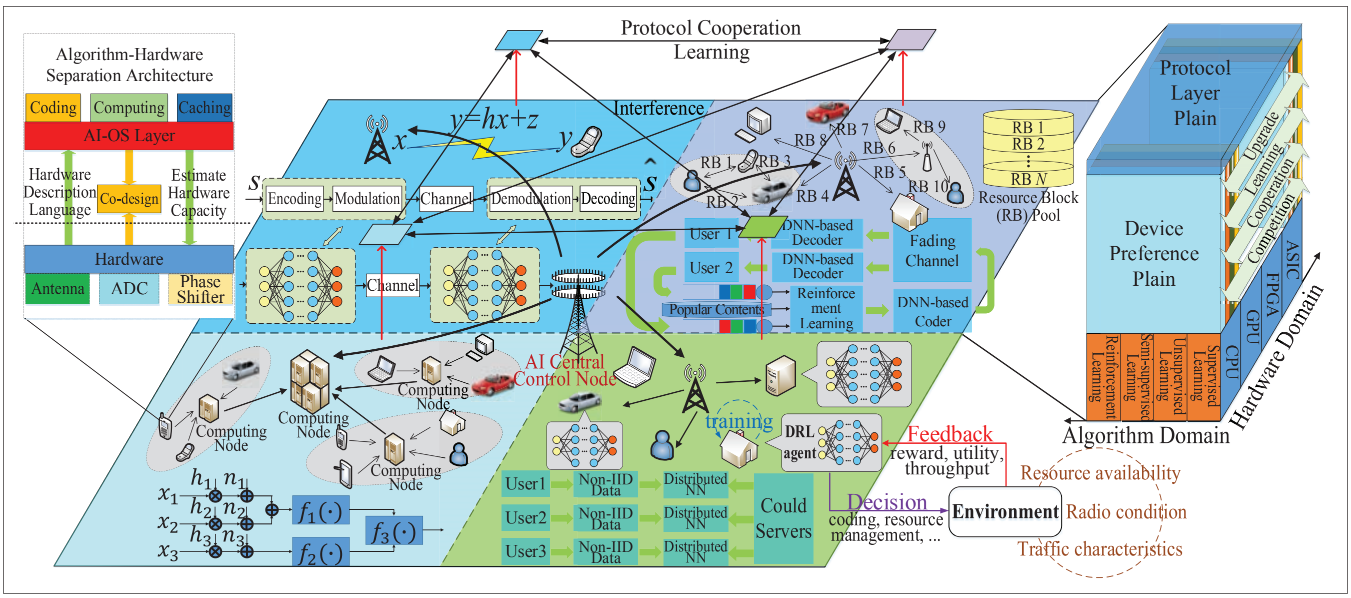

Figure 2. The architecture of 6G.

these trends, in this article, we attempt to conceptualize 6G as an intelligent information system that is both driven by and a driver of the modern AI technologies. A roadmap for 6G is depicted in Fig. 1, which is plotted based on the strategic plans of various standards bodies and is also projected based on the 5G status. Key performance indicators (KPIs) and service types are also illustrated. Meanwhile, a potential network architecture for 6G is shown in Fig. 2. We envision that AI will greatly enhance the situational awareness of the network operators, and enable closed-loop optimization to support the new service types as mentioned above. As such, 6G will unleash the full potential of mobile communications, computing, and control in a host of exciting applications, including smart cities, autonomous driving, UAVs [6], seamless virtual and augmented reality, Internet of Vehicles, space-air-ground integrated networks [7], and much more.

The Architecture of 6G Networks

In this section, we introduce a potential architecture for 6G as shown in Fig.2, in which network intelligentization, subnetwork evolution, and intelligent radio are embraced.

From Network Softwarization to Network Intelligentization

We envision that 6G will take network softwarization to a new level, namely toward network intelligentization. In 5G, the "non-radio" aspect has become more and more important, and has been the key driver behind the recent efforts on "softwarization". More specifically, two key 5G technologies are Software-Defined Networking (SDN) and Network Functions Virtualization (NFV), which have moved modern communications networks toward software-based virtual networks. They also enable network slicing, which can provide a powerful virtualization capability to allow multiple virtual networks to be created atop a shared physical infrastructure.

Nevertheless, as the network is becoming more complex and more heterogeneous, softwarization is not going to be sufficient for 6G. In particular, to support AI-based applications, the network entities have to support diverse capabilities, including communications, content caching, computing, and even wireless power transfer. Furthermore, 6G will embrace new radio access interfaces such as THz communications and intel-

Given its expected ultra-high heterogeneity, one key feature of 6G will be its capability to exploit a flexible subnetwork-wide evolution to effectively adapt to the local environments and user demands, thereby resulting in a "network of subnetworks." In particular, local subnetworks in 6G may evolve individually to upgrade themselves.

	SDR	CR	IR
Frequency band	Fixed	Adapt to environment	Adapt to environment and hardware
Spectrum sharing	Fixed	Opportunistic	AI-enabled
Hardware capability	Pre-claimed	Pre-claimed	Online estimated
Hardware upgradability	No	No	Yes
PHY Tx/Rx module	Modulation/coding/detection/ estimation	Modulation/coding/detection/ estimation	Deep neural networks
Multiple access	Predetermined	Sensing based	Distributed ML based
Protocols over Layer 3	Fixed	Fixed	Self-upgradable
Main steam apps	Voice, data	Multimedia, data	AI, in-network computation

Table 1. Comparison of SDR, CR, and IR.

ligent surfaces. It will also need to support more advanced IoT functionalities including sensing, data collection, analytics, and storage. All of the aforementioned challenges call for an architecture that is flexible, adaptive, and more importantly, intelligent. Existing technologies, such as SDN, NFV, and network slicing will need to be further improved to meet these challenges. By enabling fast learning and adaptation, AI-based methods will render network slicing much more versatile in 6G.

The design of the 6G architecture shall follow an "AI native" approach where intelligentization will allow the network to be smart, agile, and able to learn and adapt itself according to the changing network dynamics. It will evolve into a "network of subnetworks," allowing more efficient and flexible upgrades, and a new framework based on intelligent radio and algorithm-hardware separation to cope with the heterogeneous and upgradable hardware capabilities. Both of these two features will exploit AI techniques, as further illustrated in the following subsections.

A Network of Subnetworks: Local vs Global Evolution

Given its expected ultra-high heterogeneity, one key feature of 6G will be its capability to exploit a flexible subnetwork-wide evolution to effectively adapt to the local environments and user demands, thereby resulting in a "network of subnetworks." In particular, local subnetworks in 6G may evolve individually to upgrade themselves. The local evolution may happen in a few neighboring cells in order to flexibly apply cutting-edge developments on new waveforms, coding, and multi-access protocols in subnetworks without extensive time-consuming tests. In contrast to the global evolution from 1G to 5G, in which both hardware and software of all the cells are upgraded simultaneously, there is no need to find a one-size-fit-all solution for all the cells and rebuild the whole system when local evolution is exploited. To achieve this goal, we need to address the following three challenges:

- Each subnetwork should collect and analyze its local data, which may include the wireless environments, user requests, mobility patterns, and so on, and then exploit AI methods to upgrade itself locally and dynamically.
- When the local PHY or MAC protocols are changed, the inter-subnetwork interaction is expected to maintain new inter-subnetwork coordination. One possible solution is to adopt game and learning approaches, which can assure the convergence of the subnetworks upgrades.
- The local evolution of 6G requires a relatively stable control plane to support the evolution in the "network of subnetworks" level. One possible solution relies on the "learning from scratch" method developed in Alpha Zero [8].

Toward Intelligent Radio (IR)

The emerging hardware revolutions, for example, in the RF and circuit systems, will drive 6G to track and fully exploit the fast upgrade of the device-level and base-station level hardware. We envision that an algorithm-hardware separation architecture will become essential in 6G. In particular, a transceiver algorithm will be able to automatically estimate the capability of the transceiver hardware over which the protocol runs, then configure itself based on the hardware capability.

This is in contrast to the systems from 1G to 5G where the devices and transceiver algorithms are jointly designed. Conventionally, the hardware capabilities, for example, the number of antennas, RF chains, the resolution and sampling rates of ADCs, and so on, have remained quasi-static. However, the recent state-of-the-art circuits and antennas advances are speeding up and significantly improving the hardware capabilities, which make it possible for the 6G base station (BS) and handset to be diversified and upgradable. In other words, 6G will not be operating under the conventional joint design, which fails in allowing agile adaptation to a diversified and upgradable hardware.

To overcome the shortcoming of joint hardware-algorithm design and reap the benefit of the algorithm-hardware separation architecture, we present an operating system (OS) between the device hardware and the transceiver algorithms, where we can regard a transceiver algorithm as a software running over the OS. The OS is capable of not only estimating the capabilities of local RF chains, phase shifters, ADCs, antennas, and so on, but also measuring their analog parameters automatically. Based on the hardware information and AI methods, the OS will then be capable of configuring its own transceiver algorithms via an interface language. We shall refer to this framework as intelligent radio (IR). In contrast to the learning based intelligent PHY layer discussed later, IR is a much broader concept relying on the algorithm-hardware separation architecture. In Table 1, we compare key features of IR, software-defined radio (SDR), and cognitive radio (CR) [9]. IR can be regarded as a further extension of these existing approaches, in which the cutting edge AI techniques are deeply involved. The conventional modulation/coding modules in SDR/CR will be replaced by deep neural networks (DNNs) in IR, which can in an intelligent way adapt to the environment and hardware. More specifically, IR will first train its DNNs in both the transmitter and receiver side by sending labeled training data, and then transmit information bits once it meets a target performance requirement. In practice, IR provides a low-cost and flexible solution for 6G, because AI-chips have undergone a dramatic improvement most recently. An AI chip is capable of implementing DNNs in low power, thereby benefiting the DNN-based IR and leading to a paradigm-shift hardware architecture of 6G transceivers. IR also takes into account the protocols over layer 3, which are self-upgradable to support various AI applications.

By exploiting IR, 6G is expected to evaluate the contributions of various hardware components and identify their bottlenecks, which in turn helps the device manufacturers in optimizing the budget allocation of the hardware costs. As a result, the application of IR will help 6G enjoy a much reduced implementation time and a significant reduction in the cost of new algorithms and hardware, thereby speeding up its own evolution.

AI-Enabled Technologies for 6G

The unprecedented transformation of wireless networks will make 6G substantially different from the previous generations, as it will be characterized by a high degree of heterogeneity in multiple aspects, such as network infrastructures, radio access technologies, computing and storage resources, application types, and so on. In addition, the wide range of new applications will mandate an intelligent use of communications, computing, control, and storage resources from the network edge to the core. Last but not least, the volume and variety of data generated in wireless networks are growing significantly. This opens up great opportunities for data-driven network planning and operation to achieve real-time additivity to dynamic network environments in 6G, to be elaborated in this section.

Big Data Analytics for 6G

The first natural application of AI is big data analytics. There are four types of analytics that can be applied to 6G, namely descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. *Descriptive analytics* mine historical data to get insights on network performance, traffic profile, channel conditions, user perspectives, and so on. It greatly enhances the situational awareness of network operators and service providers. *Diagnostic analytics* enable autonomous detection of network faults and service impairments, identify the root causes of network anomalies, and ultimately improve the network reliability and security. *Predictive analytics* use data to predict future events such as traffic patterns, user locations, user behavior and preference, and resource availability. *Prescriptive analytics* take advantage of the predictions to suggest decision options for resource allocation, network slicing and virtualization, cache placement, edge computing, and so on. It is worth noting that harvesting and analyzing a large amount of data raise concerns about data security, privacy, ethics, and ownership. Hence, the 6G architecture and protocols shall be designed in a way that protects data security, privacy and integrity. At the same time, it is equally important that laws and regulations are established to address data ethics and ownership in the context of 6G, bearing in mind the need for a proper balance between risk and benefit.

AI-Enabled Closed-Loop Optimization

Traditional methodologies for wireless network optimization may not be applicable in 6G, as the network will be extremely dynamic and complex due to the scale, density, and heterogeneity. Modeling such systems is very hard, if not impossible. As such, traditional optimization approaches that rely heavily on mathematically convenient models will no longer be adequate [10]. Hence, the second major application of AI in 6G wireless systems is automated and closed-loop optimization. Problems in wireless networks are traditionally solved by applying sets of rules derived from system analysis with prior domain knowledge and experience. However, in the complex 6G network environment, the mapping between a decision and its effect on the physical system is cost prohibitive to define and may not be analytically available. Recent advances in AI technologies, such as deep reinforcement learning (DRL), can establish a feedback loop between the decision maker and the physical system, so that the decision maker can iteratively refine its action based on the system's feedback to reach optimality eventually. For example, the authors in [11] recently applied DRL to address several emerging issues in communication and networking, including adaptive modulation, wireless caching, data offloading, and so on, as shown in Fig. 2.

Intelligent Wireless Communication

The PHY layer of wireless communication systems suffers from a wide variety of impairments, including hardware impairments such as amplifier distortion, local oscillator leakage, and channel impairments such as fading, interference, and so on. To communicate reliably and efficiently with the combinations of hardware and channel impairments, a large number of design parameters need to be controlled and optimized jointly. Noticeably, end-to-end optimization has never been practical in wireless systems due to the high complexity. Instead, existing approaches divide the full chain into multiple independent blocks, each with a simplified model that does not accurately or holistically capture the features of real-world systems.

AI technologies open up the possibilities in end-to-end optimization of the full chain of the physical layer, from the transmitter to the receiver.

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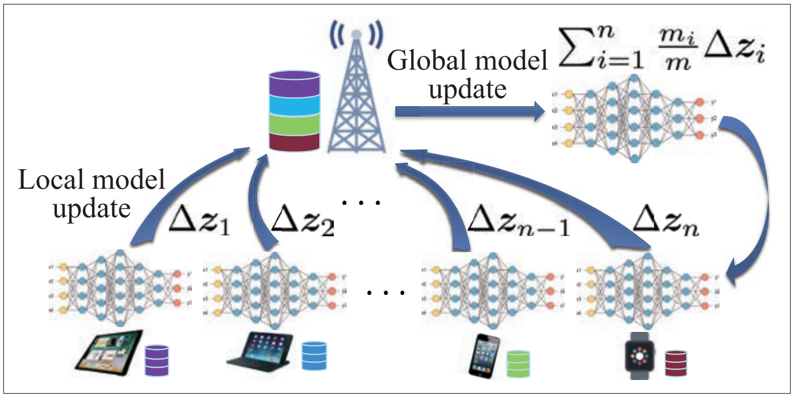

Figure 3. Over-the-air computation for on-device distributed federated learning.

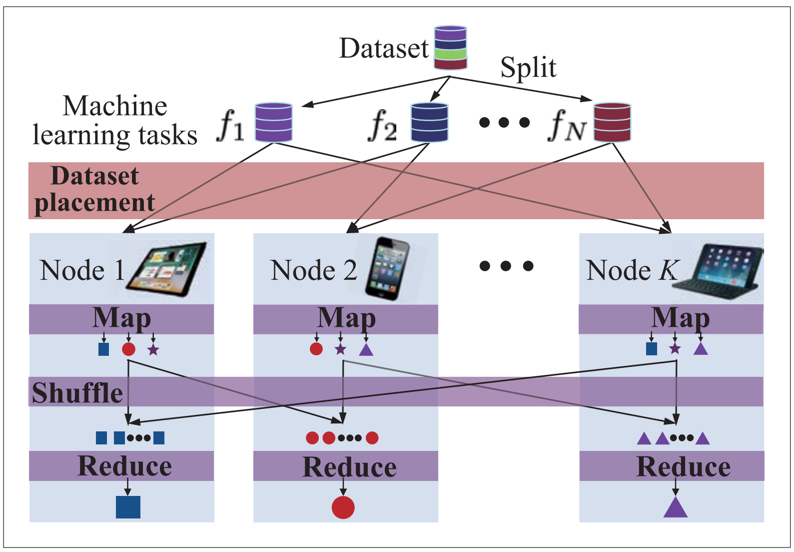

Figure 4. On-device distributed inference via wireless MapReduce.

We envision an "intelligent PHY layer" paradigm in 6G, where the end-to-end system is capable of self-learning and self-optimization by combining advanced sensing and data collection, AI technologies, and domain-specific signal processing approaches. Indeed, recent research has shown that a DNN can train the transmitter, channel, and receiver as an auto-encoder, so that the transmitter and receiver can be jointly optimized.

6G for AI Applications

With the ubiquitousness of smart mobile gadgets and the revival of AI, various AI-empowered mobile applications are emerging. In this section, we present how 6G will handle mobile AI applications.

Trends and Challenges

AI tasks are computationally intensive and mostly trained, developed, and deployed at data centers with custom-designed servers. Given the fast growth of smart mobile gadgets, it is expected that a large number of intelligent applications will be deployed at the edge of wireless networks. As such, the 6G wireless network will be designed to leverage advanced wireless communications and mobile computing technologies to support AI-enabled applications at various edge mobile devices. Notably, the capacity and latency of wireless links are the key bottlenecks of mobile AI applications due to three reasons. First, to protect privacy, some AI applications require data to be kept at the mobile devices instead of being uploaded to the cloud for model training. This has stimulated the recent research interest in on-device distributed training. Second, to overcome the resource limitation of edge devices, on-device distributed computing provides new opportunities by pooling the computation and storage resources of multiple mobile devices. In this case, data shuffling is a key component for exchanging the computed intermediate values among mobile devices [12]. Last but not least, the heterogeneous mixture of the cloud, edge and end devices provides a dispersed computing environment for both training and inference of DNNs.

To enable ubiquitous and diversified mobile AI services, 6G is expected to provide flexible platforms for developing advanced communication and computation technologies.

Communication for Distributed Machine Learning

In this section, we illustrate how 6G will address the communication challenges for large-scale distributed machine learning for mobile AI applications.

Communication-Efficient Distributed Training: The growing computation and storage power of devices provides opportunities for on-device distributed training by processing data locally. However, communicating over the volatile wireless channel becomes the significant bottleneck for distributed training on mobile devices. To strengthen data privacy and security, federated learning [5] allows the training data to be kept at each device, thereby learning a shared global model from distributed mobile devices. However, the limited bandwidth becomes the main bottleneck for global model aggregation from locally updated models computed at each mobile device. Over-the-air computation can be exploited to enable low-latency global model aggregation by exploiting the superposition property of a wireless multiple-access channel, as shown in Fig. 3. This is achieved by joint device selection (i.e., maximizing the number of selected devices) and beamforming design (i.e., minimizing the global model aggregation error) to improve the convergence rate in the distributed training process and the prediction accuracy in the inference process, respectively.

Communication-Efficient Distributed Inference: In 6G, intelligent services will span from cloud data centers to end-devices and IoT devices, for example, self-driving cars, drones, and auto-robots. To overcome stringent computation, bandwidth, storage, power and privacy constraints on individual devices, increasing research interests are moving toward leveraging the dispersed computing resources across the cloud, network edge and end-devices through the lens of mobile edge computing [13]. For example, for a DNN, the initial features can be extracted on the end devices, which are then sent to the edge and cloud computing devices for further processing. However, with the heterogeneity in the computing capabilities and communication bandwidths among the computing devices, it becomes extremely challenging to allocate the operations of the neural networks to the computing devices. Figure 4 demonstrates the on-device distributed inference process, where each device locally computes the intermediate values based on the map function using the local data. The intermediate values are further shuffled across the devices assisted by a central radio access point. The inference process will be accomplished by collecting all the required intermediate values to construct the prediction results. A joint optimization of the uplink and downlink communication strategy was thus developed in [12] for shuffling the locally computed intermediate values across mobile devices.

Hardware-Aware Communications for 6G

As new radio access technologies emerge, and IoT devices become more pervasive, hardware constraints will play critical roles when designing 6G networks. On one hand, as radio communication is moving toward millimeter-wave (mmWave) Terahertz bands, the high cost and power consumption of hardware components will significantly affect the transceiver architecture and algorithm design. On the other hand, IoT devices have limited storage, energy source, and computing power. Such resource-constrained platforms call for a holistic design of communication, sensing, and inference. In this section, we present a new design paradigm for 6G, namely *hardware-aware communications*, and discuss three promising new design principles.

Hardware-Algorithm Co-Design

The desire to communicate at ever higher data rates will never stop. To reach Terabytes per second data rates, it is inevitable to operate at higher and higher frequency bands. Very large scale antenna arrays are needed to overcome the increased pathloss and other propagation phenomena, which require the support of various hardware components, including signal mixers, ADCs/DACs, power amplifiers, and so on. The high cost and power consumption of these components at the mmWave and THz bands make it difficult to adopt conventional transceiver structures, which in turn will affect the design of signal processing algorithms. To effectively design such complex systems, collaboration among the hardware and algorithm domains will be needed, that is, hardware-algorithm co-design should be advocated. The target is to develop hardware-efficient transceiver structures that are also algorithm friendly. While such a hardware-algorithm co-design approach has been partly adopted in previous generations of cellular networks, it will play a more important role in 6G, assisted by AI-based methods.

Case Study: Consider mmWave hybrid beamforming as an example, which is a cost-effective approach for providing effective beamforming gains. It requires a small number of RF chains, and thus can significantly reduce hardware cost and power consumption. However, a large number of phase shifters are still needed for the existing hardware structure. Phase shifters at mmWave bands are still expensive, and thus their number needs to be reduced. A new hardware-efficient hybrid structure was recently proposed in [14], as shown in Fig. 5. It only requires a small number of phase shifters, each with a fixed phase.

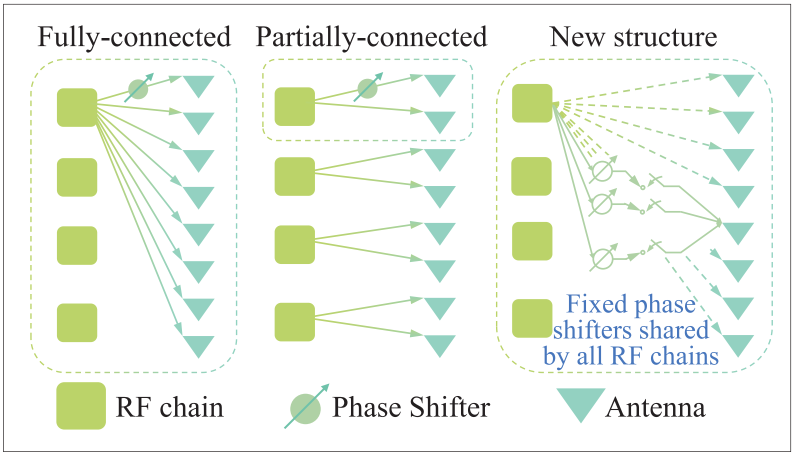

Figure 5. The comparison between three different hybrid beamforming structures. The conventional fully-connected and partially-connected structures suffer from high hardware complexity and significant performance loss, respectively. The new structure proposed in [14] achieves performance close to fully digital beamforming, with a small number of fixed phase shifters.

As such, hardware modification is only in the analog network and thus basic design principles for hybrid beamforming can still be applied. As shown in [14], this new structure can approach the performance of the fully digital beamforming, with much fewer phase shifters than other hybrid beamforming structures.

Application-Aware Communications for IoT Devices

Thanks to the recent development of IoT technologies, intelligent mobile applications will thrive, and many of them are powered by specialized low-cost, low-power devices. Such devices can only handle basic sensing and processing tasks, while relying on proximate edge servers or remote cloud data centers for computation-intensive processing. Thus, effective communications between devices and servers will be essential. Rather than serving as a bit pipe for traditional data services and focusing on maximizing data rates, wireless communications for IoT applications should directly serve specific applications. One solution is illustrated below.

Joint Sampling, Communication, and Inference: IoT devices face serious challenges, that is, limited computing power, limited energy supply, limited storage space, and constrained communication capability. By jointly optimizing sampling, communication, and local processing, and accounting for the state of local processors, storage, and channel states, the overall performance can be improved. The integration with edge computing [13] will play an important role, and joint edge-device processing techniques will play important roles.

Intelligent Communications for Heterogeneous Hardware Constraints

Wireless networks are getting more and more heterogeneous, with various types of access points and mobile terminals. Such heterogeneity has started from 4G LTE networks, and with the deployment of advanced techniques such as massive MIMO, the situation will further develop through 5G, and into 6G. This trend will complicate the communication protocol and algorithm

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design. Recently, adopting machine learning techniques to develop communication systems has demonstrated its effectiveness, and such approaches have the potential of leading to general purpose intelligent communications that can adapt to heterogeneous hardware constraints. A particular approach is illustrated as follows.

Transfer Learning for Different Hardware Constraints: One complication brought by hardware heterogeneity is the excessive effort to redesign the system for different hardware settings. For example, different transceiver architectures have been proposed for mmWave systems, including analog beamforming, hybrid beamforming, and 1-bit digital beamforming. The conventional approach relies on a hand-crafted design for each of them, which is very inefficient. These different types of transceivers will face the same physical system, and thus an algorithm well designed for one may also shed light on the design for another. Transfer learning is a promising technique that can help transfer the design of one architecture to others.

Conclusions

This article is a humble attempt to provide a forward looking research roadmap for 6G. New features of the 6G evolution were identified, and enabling technologies were discussed. While a partial picture was presented, we hope our discussion will spur interests and further investigations on the future evolution of cellular networks.

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