Artificial-Intelligence-Enabled Air Interface for 6G: Solutions, Challenges, and Standardization Impacts

Shuangfeng Han, Tian Xie, Chih-Lin I, Li Chai, Zhiming Liu, Yifei Yuan, and Chunfeng Cui

Abstract

As 3GPP has completed Release 16 specifications and worldwide 5G commercialization is speeding up, global interest in 6G is starting to grow. An interesting and important question is: will the rapid progress in artificial intelligence (AI) eventually alleviate the tremendous efforts required for future standardization of 6G and beyond? In this article, the potential impacts of AI on the air interface design and standardization are investigated. The AI-enabled network architecture is first discussed. The higher layer, physical layer, and cross-layer design empowered by AI capability are further presented. Based on these designs, the future 6G and beyond are expected to enter into an AI era. For potential new use cases and more challenging requirements, the network is capable of automatic updating the air interface protocols, which may substantially reduce the standardization efforts and costs of wireless communication networks.

Introduction

Wireless communication networks have been evolving from the first generation (1G) to the current fifth generation (5G) to satisfy the ever-increasing demands of mobile traffic [1]. According to the newly released 5G New Radio (NR) specs from the Third Generation Partnership Project (3GPP), new concepts and solutions have been studied or adopted, including, for example, the service-based network architecture, two-layer centralized unit/distributed unit (CU/DU) radio access network (RAN) architecture and signaling interfaces [2], and so on.

To many researchers and engineers, a natural and important question is, "Will 6G possibly come around in 2030, and what will its outstanding features be?" Given the historical trend from 1G to 5G, there will be even higher requirements for 6G networks [3], for example, peak data rate of terabits-per-second level, spectrum efficiency 2–3 times that of 5G, user experienced data rate of 10–100 Gb/s, user plane latency of less than 0.1 ms, and mobility support of higher than 1000 km/h. Meanwhile, 6G is expected to be on the verge of the all-pervasive wireless Internet of Everything, capable of supporting mobile traffic in diversified scenarios with mixed key performance indicators. Following the current trend of standardization, one overwhelming fact is that for each generation of wireless cellular communications, the total cost in replacing the hardware and software of the RAN and the core network (CN) with the new versions will tremendously increase, which places heavy burdens on the operators.

It is anticipated that artificial intelligence (AI) will play a critical role in future 6G networks. In [3], "pervasive intelligence" is proposed as one of the ultimate goals for the 6G network, which helps to form an auto-generating and auto-configuration network paradigm. The authors in [4] envisioned 6G with ubiquitous AI services ranging from the CN to the end devices. In [5], several top challenges toward AI-enabled 6G were outlined to highlight future research in this field. The industry has also begun to explore the use of AI techniques in wireless networks. 3GPP launched study items on network data analytics function (NWDAF) and big-data-driven network architecture for 5G to anticipate a customized and improved service delivery via traffic characteristic identification [5]. However, the AI-enabled air interface design is not within the current scope of 3GPP, because the study on AI-enabled physical layer design is still in its infancy, and the framework of network architecture, the protocol layers, and the physical layer of 5G has largely been frozen. Therefore, while AI can be applied to some extent to 5G, it is 6G that would provide more room for AI to unleash its potential [6].

In this article, we mainly investigate the impact of AI techniques on the wireless RAN. Despite brilliant studies investigating how to apply AI to RAN functions, there is little work on how the air interface design and standardization would be impacted by these AI techniques. For future wireless communications, is it possible that the evolution or revolution of standardization can be substantially facilitated by the booming AI technologies so as to upgrade in an automatic way? For potential new use cases and more challenging requirements, the network is expected to automatically configure the processing algorithms, signaling, and protocol procedures, which could substantially reduce the standardization efforts and costs in deploying new network infrastructures.

The authors investigate the potential impacts of AI on the air interface design and standardization. The AI-enabled network architecture is first discussed. The higher layer, physical layer, and cross-layer design empowered by AI capability are further presented. Based on these designs, the future 6G and beyond are expected to enter into an AI era.

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Digital Object Identifier: 10.1109/MCOM.001.2000218

 0163-6804/20/$25.00 © 2020 IEEE

The contribution and structures of this article are summarized as follows. First, the AI-enabled network architecture is presented, which is able to configure RAN functions and intelligent real-time scheduling to provide flexible, elastic, customized, and on-demand resource management. Second, AI-enabled physical (PHY) layer processing is examined. Based on the presented example as well as other convincing studies on AI-enabled PHY design, we envision an "artificial intelligence plus human intelligence (AI+HI)" framework for future air interface design. After that, AI-based cross-layer optimization is proposed, where the air interface status information and application characteristics are analyzed to facilitate joint optimization. Finally, this article is concluded.

AI-Enabled Network Architecture and Higher Layer Design

Motivations

There have been a number of studies on how to apply AI techniques (especially the emerging machine learning techniques) in RAN design. As summarized in [7], machine learning could play an important role in radio resource management/control (RRM/RRC), mobility management, networking, and so on. If we take the power control issue in spectrum sharing systems as an example, at least three kinds of approaches are available: reinforcement-learning-based approaches, supervised-learning-based approaches, and transfer-learning-based approaches. Reinforcement-learning-based approaches tend to directly learn the power control policy through interactions with the system environment, where Q-learning is the most widely used tool. In contrast, supervised-learning-based approaches aim to efficiently solve the complex non-convex optimization problem via neural network unfolding methods. Transfer-learning-based approaches are somewhat similar to the reinforcement-learning-based approaches, but put more emphasis on reusing the learned models in other cells with similar settings. For more detailed technical elaborations, one can refer to [6, 7, references therein].

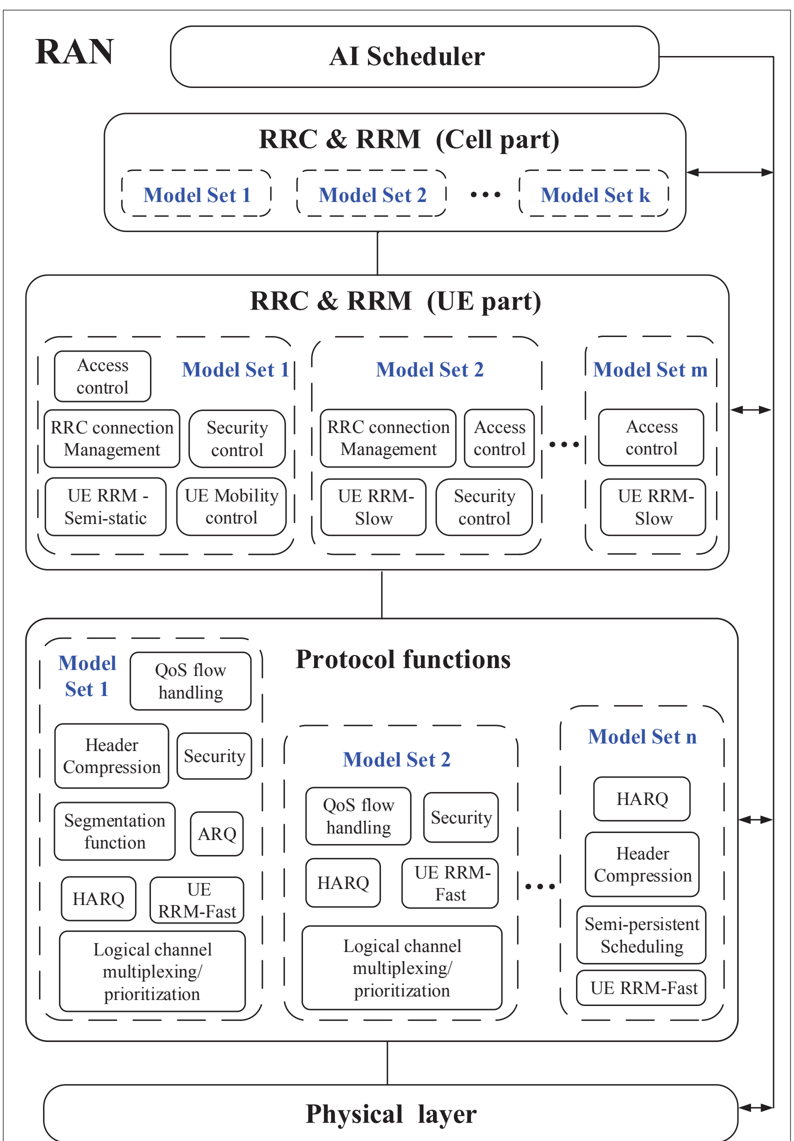

Figure 1. Proposed AI-enabled RAN architecture.

However, it is not trivial to implement the aforementioned impressive studies in practical networks. The existing RAN architecture and associated interface design did not reserve sufficient design flexibility for future potential network enhancements using AI approaches. For example, operators could find it difficult to improve the scheduling mechanisms with user knowledge learned via big data analytics [8], since the RRM and medium access control (MAC) scheduling algorithms of their network have been implemented by vendors, and there is no such open interface available for potential improvements. In addition, the emerging services could require not only high data rate and ultra reliability, but also high positioning sensitivity and frequent interactions with users. Consequently, frequent release update is needed for the conventional vertically hierarchical protocol stack architecture to cope with these emerging services, which incurs significantly more efforts in the standardization process. Therefore, a new RAN architecture is urgently demanded to activate the potential gains brought by AI techniques, as addressed in the following subsection.

AI Enabled RAN Architecture

To alleviate the burden of standardization and maximize the potential gain of AI-enabled network optimization, we propose an AI-enabled RAN architecture. As shown in Fig. 1, the RAN functions are controlled by one AI scheduler, which determines all the necessary RRC, RRM, protocol function elements (PFEs) configuration, and MAC layer scheduling. Compared to the traditional RRC, RRM, and MAC scheduling, this AI scheduler features more intelligent algorithms:

- Intelligent service identification: The services' characteristics can be learned by various AI techniques including deep learning, reinforcement learning, Q-learning, and so on. This information will enable the MAC scheduler to use more intelligent policy and algorithms.
- Intelligent protocol functions selection.
- Powerful MAC scheduling: The scheduler could be more efficient and intelligent based on the potential prediction of channels, data traffic, quality of service/quality of experience (QoS/QoE) indicator, and so on at either the AI controller or AI scheduler.

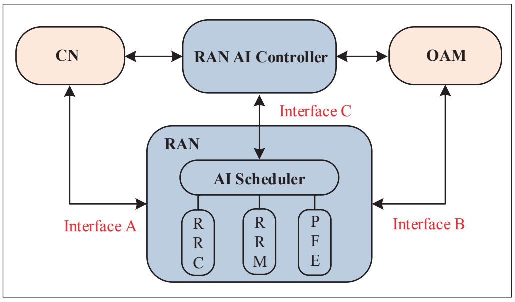

Figure 2. Architecture of an AI-enabled wireless network.

- Intelligent physical layer functions: For example, AI-enabled channel coding and more advanced receivers are possible with AI capabilities.

In this way, the proposed architecture is able to transform the existing hierarchical protocol stack into a certain set of modularized PFE, thus providing flexible, elastic, customized, and on-demand resource management to meet the diversified services' requirements.

The high-level architecture of an AI-enabled network is illustrated in Fig. 2. The RAN AI controller is responsible for the non-real-time AI processing and has logical interfaces with the CN, network operations, administration and maintenance (OAM) platform, and base station (BS). Via big data analytics [8], the AI controller is able to predict user mobility, traffic behavior, network loading fluctuation, and so on, which will then be sent to the BS to help the AI scheduler manage the RRC, RRM, PFE orchestration, and real-time MAC scheduling. The PFE may include all the necessary functions as specified in the 4G and 5G protocol stacks, such as hybrid automatic retransmission request (HARQ), header compression, and segmentation. The potential functions that will be needed in the future can also be included. Note that the AI controller and AI scheduler are logical entities or functions, and can be physically implemented in the same entity like the CU. Furthermore, the AI controller can also be implemented in the OAM platform to have global intelligence capability and interact with the AI scheduler at BSs.

The AI scheduler is at the core of the proposed RAN architecture, which could dynamically tailor and optimize the RAN by interacting with other basic RAN functions. There are two main types of interactions between the AI scheduler and other RAN functions.

Interaction with RRC and RRM Mechanisms: The AI controller and AI scheduler could utilize deep learning techniques based on historical data and new data to figure out a customized RRC and RRM functions set for a given UE in a specific scenario. For example, in model 2 of RRC function and RRM for the UE part in Fig. 1, if the AI controller detects that parts of the UEs are basically static for a certain time period through big data analytics, it can (re)train the models of RRC and RRM functions to relax or cancel the RRM measurement reporting and mobility control functions to simplify the UE mobility control process. Moreover, if the AI controller detects that some UEs' service always requires super-low latency, the traffic pattern of the UE is difficult to predict, and the data volume is not very high, the AI scheduler will force UEs into RRC inactive mode instead of RRC idle mode and especially RRC connected mode in some cases. At the same time, the AI controller can directly route the UEs' traffic to the local content, rather than the cloud content, to reduce the latency.

Interaction with Other Protocol Function Elements: In addition to the above RRC and RRM schemes, the AI scheduler is also responsible for the configurations of the PFE for a specific service. From all the available PFEs, the scheduler will select a set of PFEs considering all the necessary information, for example, the non-real-time application layer traffic characteristics and requirements, the near-real-time user network-side transmission indicator information, the real-time physical transport block (TB) resource information, and so on. The above information could be efficiently obtained via applying popular machine learning approaches on traffic flows from the application layer, transport layer, or MAC and PHY layer. For example, based on a UE's traffic pattern learned from application layer data, the network can directly allocate a reserved semi-static resource, such as semi-persistent scheduling (SPS) and configured grant (CG) configuration(s), to the UE, instead of regular dynamic scheduling, as shown in model set *n* of protocol functions in Fig. 1. Similarly, a service's specific requirement on reliability and survival time could also be reported, which helps the scheduler determine whether to trigger a duplication mechanism or repetition transmission for UEs.

Potential Standardization Impact and Future Challenges

For the proposed AI-enabled RAN architecture, parts that need to be standardized may be significantly reduced in the long run compared to LTE and 5G NR systems. The mandatory features (which have been specified well in the current standards), the interfaces between the mandatory features and AI scheduler (i.e., interface A between the AI controller and CN, interface B between the AI controller and OAM, and interface C between the AI controller [non-real-time] and AI scheduler [real-time or near-real-time], as illustrated in Fig. 2, need to be standardized. In contrast, optional features that are handled by the AI scheduler do not need to be standardized. This is particularly important, since many future functions/features can be realized without or with much reduced human efforts.

As more and more studies confirm the benefits of using AI techniques in RAN design, we need to put more efforts into addressing the implementation issue of these AI-enabled solutions in real-world networks. In addition to continuing our research on classic but critical issues such as data collection in wireless networks, we need to further think about how to better support AI-based RAN solutions in terms of interface design and network architecture, and leave enough freedom for future emerging solutions. Only after solving these practical issues will we be able to truly validate the benefits of AI techniques in wireless networks. At present, the industry has shown much interest in the above issues, and has conducted

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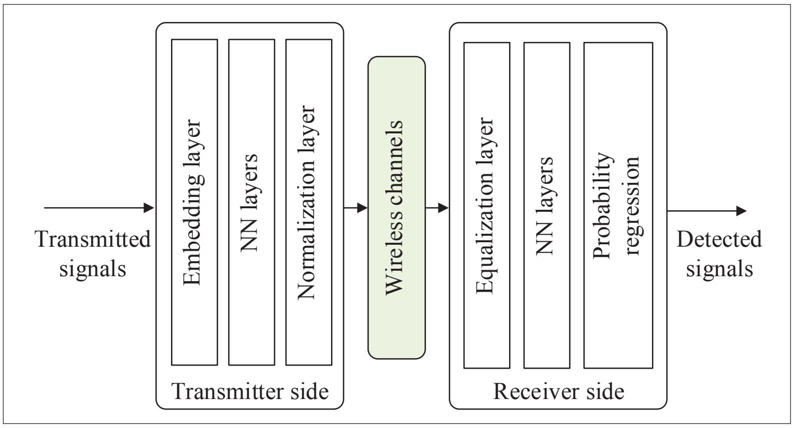

Figure 3. An illustration of an NN implemented transceiver [9].

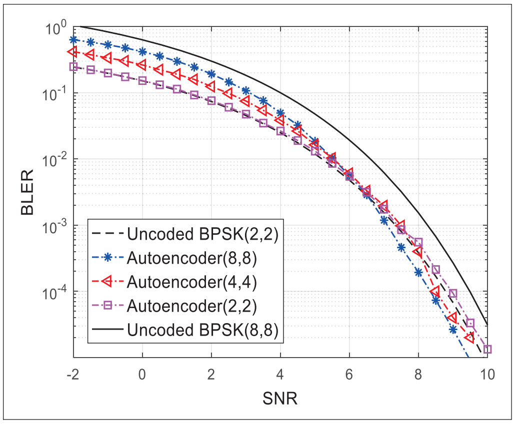

Figure 4. Performance comparison between two transceiver implementations.

some initial exploration, such as the radio intelligence controller (RIC) investigated in the Open-RAN (O-RAN) alliance. However, the preliminary results are still controversial. In the future, joint efforts from industry and academia are highly advocated to address these issues.

AI-Enabled Physical Layer Design

AI-Enabled Transceiver Implementation

Physical layer transceiver design has taken the form of a sequential module-by-module realization since the initial commercialized communications. However, heavy and complicated internal interfaces and control signaling are required to enable the data signals to fluently flow among these modules, which makes the PHY layer design more bloated during the evolution of cellular communications. Although the joint design and optimization of a number of modules have been considered, the complexity of such schemes is usually significantly high.

The emerging AI-enabled PHY layer design is a promising approach to relieve the above issue. As proposed in [9], advanced artificial neural networks (NNs) in deep learning can be used to jointly optimize a number of physical layer modules. As an example, Fig. 3 demonstrates a simple system communicating over an additive white Gaussian noise (AWGN) channel, which is implemented via an auto-encoder NN structure.

In Fig. 4, the performance of the NN implemented transceivers is presented to illustrate its feasibility, where the transceivers are both implemented through two-layer sequential fully connected NNs. As a simple differentiable AWGN channel is considered, classical training algorithms in deep learning can be adopted to train the NN in an end-to-end manner. In our experiment, an Adam optimizer is adopted in a 7 dB signal-to-noise ratio (SNR) environment to minimize the overall error rate of restoring messages at the receiver. During the training stage, 1e6 training data samples generated from simulation are utilized, each of which is composed of a transmitted symbol, a received symbol, and an AWGN chan nel realization. Note that as we do not consider online adaptation in our example, it is unnecessary to retrain the model. However, online adaptation plays an important role when deploying AI-enabled PHY layer solutions in practical systems, where model retraining according to real-time online data is a common approach. More discussions toward the online adaptation issue can be found in [10, 11, references therein].

From Fig. 4, we can see that the optimized NNs are able to accomplish transmitting messages over an AWGN channel with almost the same performance compared to legacy modulations. Moreover, as the dimension of the system increases, the NN implemented system outperforms the quadrature amplitude modulation (QAM) system, since a correlation between output symbols of the transmitter has been learned during the training [10]. In fact, the correlation between output symbols learned by NNs is similar to a kind of channel coding with short length.

Based on the transceiver architecture shown in Fig. 3, we can further jointly optimize the dimensions and patterns of the modulation constellations under specific SNRs, which helps to achieve a better trade-off between error rate and spectral efficiency in link adaptation. Particularly, given a specific SNR, we can train the transceivers to obtain the optimized constellation patterns regarding different constellation dimensions (i.e., the input message types). Note that the dimension of constellations in an NN implemented transceiver can be any integer rather than constrained to a power of 2. Then the most suitable dimension and the corresponding pattern can be selected from the candidates to maximize the objective functions while satisfying an error rate constraint.

Figure 5 gives an example of the joint optimization of constellation dimensions and patterns. In this case, the best constellation is chosen to maximize the expected transmitted bits under an error rate threshold of 10^{-1}, and the maximum modulation order is set to 16. The expected transmitted bits are defined as the product of the error rate in the given SNR and the transmitted bits (i.e., $\log_2^M$), where M is the dimension of the constellation. For the baseline scheme, an adaptive modulation among quadrature phase shift keying (QPSK), 8-QAM, and 16-QAM is adopted. From Fig. 6, it can be found that the adaptive modulation among constellations optimized via AI approaches generally outperforms the conventional method, since more choices for constellation dimensions are supported. More importantly, we find that an AI-optimized constellation with 8 (16) dimensions is adopted at 9 (12) dB SNR as illustrated by the ellipses in Fig. 6, while, in contrast, QPSK (8-QAM) is still chosen for the same link condition. This phenomenon suggests that the constellations designed by AI methods (Fig. 5) could achieve a better error rate than the conventional QAM constellations with the same dimension, especially in high order regions (e.g., 8 or 16 points).

It is worth pointing out that deep learning techniques can also be utilized to enhance other PHY layer functions. For example, the authors in [12] leveraged deep learning techniques in channel coding design, where the NN was designed based on the "turbo principle" in classical turbo codes. The proposed deep learning enhanced codes in [12] are able to approach near-optimal performance under canonical channels and even demonstrate better reliability than some state-of-the-art codes under non-canonical channels. In addition, deep learning has shown significant potential in massive multiple-input multiple-output (MIMO) signal processing enhancement. In [13], the authors proposed to employ convolutional neural networks (CNNs) to explore channel correlations in the spatial, temporal, and frequency domains to improve the estimation accuracy and reduce overhead. More studies in this field can be found in [14, references therein]. Distinguished from the auto-encoder-based transceiver implementation, studies introduced in this paragraph mainly concentrated on specific air interface function enhancement more compatible with the conventional module-by-module framework.

In the above discussion, our first concern is whether the AI-enabled PHY layer solutions could improve the transmission performance (i.e., the block error rate). Meanwhile, it is also essential to pay enough attention to other performance indicators such as the processing delay, which plays a critical role in a number of ultra-reliable and low-latency communication (URLLC) scenarios. As the structure of the NN is naturally suitable for parallel computing, there are papers discussing its potential advantage in low-latency communication [14]. Nevertheless, convincing conclusions on this issue should be drawn based on results from field trails. More future efforts from both academia and industry are needed to address these open questions.

Impact on Standardization

It is anticipated that the new features brought by AI-enabled PHY layer design will significantly impact future standardization. First of all, since a number of function modules can be merged through AI, the complicated internal interfaces could be significantly simplified. Second, as the basic PHY layer functions can be realized through AI approaches and optimized in a self-learning manner, man-made efforts will mainly focus on the general framework designs. Additionally, the AI-enabled PHY layer design strongly evokes the application of general hardware, which could implement various functions/algorithms with similar hardware architecture. The utilization of general hardware offers much convenience in wireless network upgrade, which helps to reduce the network deployment and maintenance costs. Note that similar trends can be found in the undergoing 5G networks, where network function virtualization (NFV) has been introduced to decouple core network functions and hardware to save the costs of network updating and maintenance.

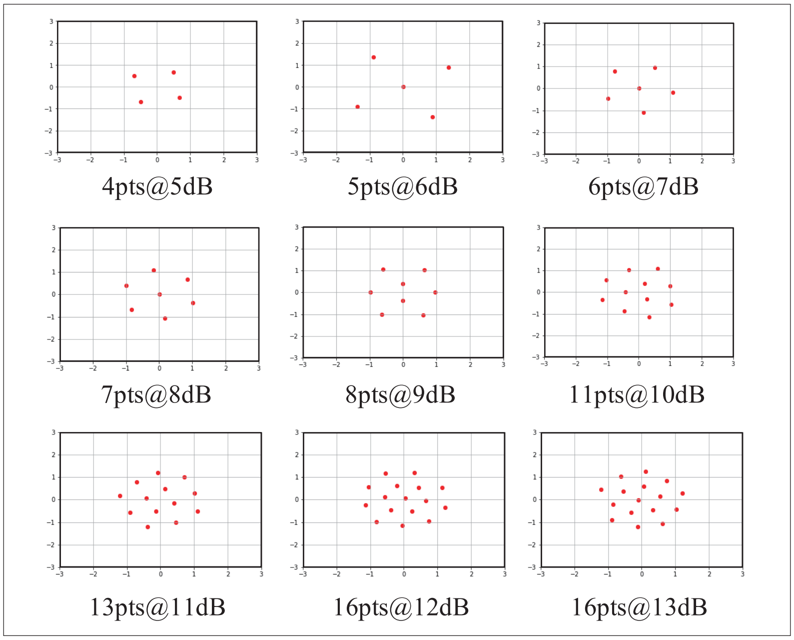

Figure 5. Optimized constellation patterns.

However, it is challenging for purely AI-based communications to operate in the practical wireless environments. For example, it is difficult for AI to learn how to communicate under multi-path channels, which is a common problem in communications. These issues, however, have been well addressed by human expert knowledge in the last few decades. Therefore, the integration of human intelligence (HI) and AI may be necessary for PHY layer design. For example, the basic frame structure, downlink and uplink synchronization signals, reference signals, measurement report mechanism, physical layer procedures, and so on need to be designed properly by HI. Therefore, while we believe that AI is sure to have huge or even disruptive impacts on the PHY layer standardization, it should be admitted that the changes would come in a progressive manner. In the initial stage of this progress, AI tends to serve as an auxiliary tool or optimizer to enhance certain PHY layer functions. The application of AI tools in physical layer standardization might first occur in physical layer resource management, for example, power control or beam management.

AI-Enabled Cross-Layer Optimization

AI will help realize collaborative traffic optimization between operators and over-the-top (OTT) players. This can not only improve user experience but also create new economic growth. Different from the traditional cross-layer optimization, which only enables simple open capability from the wireless network to applications [15], the AI-enabled higher layer will open up more opportunities between the wired and wireless worlds through the bidirectional interaction mechanism between BSs and application layer/transport layer.

Generally, there are two modes BSs can select to report status information to the application

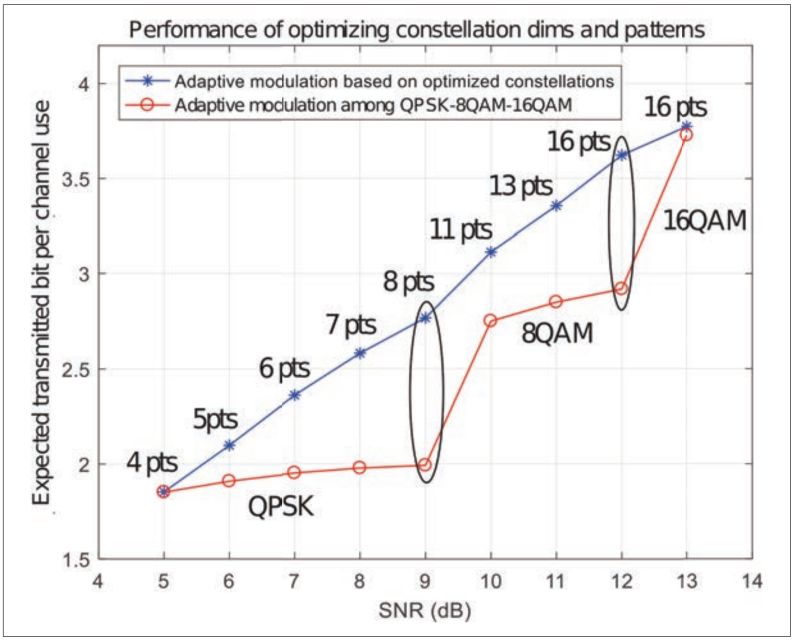

Figure 6. Comparison of expected transmitted bits per channel use.

layer/transport layer: periodic mode (e.g., every 100 ms) and event-triggering mode. The network fluctuation caused by unexpected events will have a significant impact on the user experience. For example, in the early stage of 5G, 4G and 5G networks will coexist. As the UE switches from 5G to 4G, the available radio resources are likely to suddenly shrink due to the limited capability of 4G. Because the applications cannot sense this change in time, the server or user will not be able to make adjustments in time and the user experience will deteriorate. As different applications require different status information (e.g., bandwidth, round-trip time, and packet loss rate), traditional cross-layer optimization can only access simple and universal capabilities that are not tailored for the specific traffic types. If a number of wireless capabilities are blindly opened at the same time, it will increase the burden of the BS, even wasting resources or causing confusion at the application layer. Relying on the AI function, the BS can open different capabilities on demand and in time for different transport layer settings, which can perform traffic and rate adjustment directly based on such information.

The application layer can deliver traffic characteristics information to BSs. Then the AI module of the RAN is able to utilize the collected data to conduct traffic modeling (e.g., wireless QoE modeling). The QoE model will directly act on the optional features of the flattened higher layer, enabling different combinations of optional features and corresponding operations of the protocol stack. The air interface can be optimized by inputting the application layer information obtained by the AI module in real time into the QoE model. The AI module needs to comprehensively determine whether there are resources to meet the application requirements and whether it is suitable to change its scheduling priority. At the same time, the AI module can use the multi-user QoE model to determine whether the network needs to be expanded, and monitor the load balancing.

Conclusions

To meet the ever-increasing mobile communication requirements in an economic manner, general-purpose hardware of the wireless network infrastructure with AI-enabled communication protocol, signaling, and data processing is anticipated to bring a paradigm shift of the air interface standardization. The traditional intensive efforts on physical and higher layer standardization may well be greatly alleviated, and the communication society may enter the AI era from 6G onward.

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