ARTIFICIAL INTELLIGENCE FOR RIS-AIDED WIRELESS COMMUNICATIONS

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Abstract – *The recently proposed Reconfigurable Intelligent Surface (RIS) can reconstruct the wireless channels between the transceivers, thus it is regarded as a promising technology for future 6G wireless networks to enlarge their coverage and improve the capacity. However, RISs also impose some new challenges, such as an unaffordable overhead for channel estimation and high complexity for real-time beam-forming. Fortunately, the impressive success of Artificial Intelligence (AI) in various fields has inspired its application in RIS-aided communications to address these challenges. In this paper, two pairs of dominant methodologies of using AI for RIS-aided wireless communications are discussed. The first one is the AI-based algorithm design, which is illustrated by some examples of typical transmission techniques. The second one is the AI-based architecture design, which breaks the classical block-based design rule of wireless communications in the past few decades. The interplay between AI and RIS is also highlighted. Finally, key challenges and future opportunities in this emerging area are pointed out. We expect that this paper will stimulate more promising AI-based investigations for RIS-aided wireless communications.*

Keywords – Artificial intelligence, beam-forming, channel estimation, reconfigurable intelligent surface (RIS)

1. INTRODUCTION

Recently, an emerging technique called Reconfigurable Intelligent Surface (RIS), also named Large Intelligent Surface (LIS), Intelligent Reflecting Surface (IRS), or programmable metasurface, has attracted extensive research interest in the wireless communication society. Specifically, RIS is a class of special surfaces that can reconfigure the propagation of Electromagnetic (EM) waves [1]. A typical RIS consists of a large number of low-cost and passive elements, which are able to reconfigure the EM propagation by changing the phases, amplitudes, or frequencies of incident waves, and then re-radiate the tuned EM waves back to the environment. To fully exploit the possible capacity gain brought by RISs, a estimation of high-dimensional RIS channel [2] and passive beamforming for design for RIS [3] are two essential signal processing components of RIS-aided wireless communications. However, since a large number of RIS elements are usually required to improve the communication capacity, these two components will result in an unaffordable overhead for channel estimation and computational complexity for beam-forming design. As a result, some new methodologies are desired to address these challenges.

Artificial Intelligence (AI) has achieved impressive successes in diverse fields, such as image recognition, self-driving vehicles, and so on [4]. The excellent success of AI has inspired interest in the application of AI to RIS-aided wireless communications. Specifically, Deep Learning (DL) with enough hidden layers is capable of approximating any continuous functions with arbitrary accuracy, even those functions that are difficult to be precisely described by mathematical models. Thus, we are able to solve some problems without exact models utilizing this feature. For example, in the multi-RISs scenario with sufficient scatterers, where the signal may radiate to different RISs and scatterers, accurate channel modeling is challenging. Moreover, AI methods are well-known for their computational efficiency, which provides a powerful tool to meet the challenging requirement of real-time communications. Therefore, AI is attractive for addressing large-scale RIS-aided wireless problems.

In this paper, we will discuss how to apply AI for RIS-aided wireless communications by introducing two pairs of design methodologies, i.e., AI-based algorithm design and AI-based architecture design. In particular, AI-based algorithm design is able to reduce the overhead or speed up the algorithmic processing. This design methodology is illustrated by several transmission algorithm designs for RIS-aided communications. Moreover, AI-based architecture design utilizes AI to reform the classical block-based communication design principle. This methodology is supported by revolutionary joint transceiver design based on AI, which consists of two classes: DNN-assisted transceiver design and DNN-like transceiver design. The principles, features, and performance of these AI-based designs will be discussed in this article. More importantly, the interplay between AI and RIS will be highlighted in this article.

The rest of this article is organized as follows. Section 2 provides the key features of RIS. The details of AI-based algorithm design and the architecture design are investigated in Section 3. Challenges and future opportunities are discussed in Section 4, where the interplay of AI and RIS is presented. Finally, conclusions are drawn in Section 5.

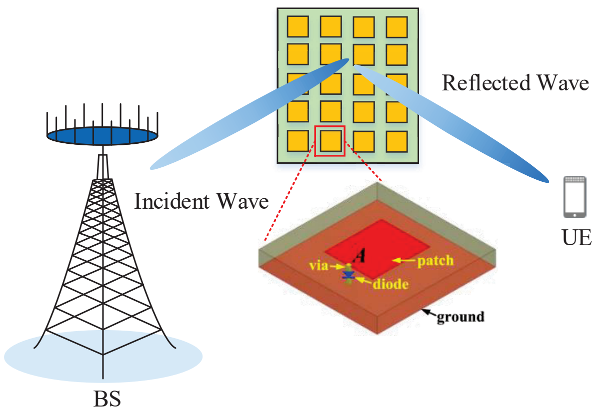

Fig. 1 – An example of RIS-aided wireless communications [1]

2. KEY FEATURES OF RIS

The system model and the basic structure of an RIS are shown in Fig. 1 [1]. RIS is able to generate real-time directional beams to different users in by individually manipulating the phase shifts of elements, which may build a new paradigm of controlling the wireless environment in future wireless networks. The following advantages are expected by employing RIS in wireless communications.

First of all, RIS can overcome the blockage to a certain extent. Specifically, RIS is able to rebuild the channel link blocked by obstacles as a reflective relay. Thus, RIS can enhance the wireless link robustness. Secondly, the coverage can be expanded by employing RIS in complicated propagation environments, especially in high-frequency communication scenarios. With the increase of working frequency, the severe propagation attenuation at high frequencies will lead to a cliff-like drop in received signal power. RIS can be deployed to provide an additional communication link to provide extra power for distant user equipment (UE). Moreover, due to the passive elements, RIS provides an energy-efficient alternative of the traditional Base Station (BS) or energy-hungry phased array.

Even though RIS has a lot of advantages as mentioned above, the deployment of RIS meets many barriers in practice. First of all, as RIS has a large amount of passive elements without signal processing capability, the overhead of key transmission techniques in an RIS-aided wireless communication system is unaffordable. Moreover, RIS with discrete phase shifts is preferred in practice. This will make the transmission algorithm design of RIS-aided wireless communication systems non-convex. Even though some iterative optimization algorithms can be applied to solve the problem, the computational complexity is usually unaffordably high. Last but not least, in past decades, the block-based design principle has dominated the wireless communication system design. In a block-based design system, there are several functional blocks optimized with mathematical model and expertise independently. It is difficult where the optimization problem of the wireless communication system to converge to global optimum. Since the design of RIS-aided wireless communications is even more complex than the wireless communications without RIS, it is harder to converge to global optimum for RIS-aided wireless communications. Fortunately, as the AI shows excellent performance in solving the non-convex problems with high computational efficiency, it may offer an elegant solution to these challenges.

3. AI-BASED DESIGN FOR RIS-AIDED COMMUNICATION

In this section, we will discuss dominant RIS-aided wireless communication systems assisted by AI schemes by classifying them into two categories: AI-based algorithm design and AI-based architecture design. Specifically, AI-based algorithm design adopts the AI method for specific transmission techniques of RIS-aided wireless communications. For the AI-based architecture design, jointly AI-based transceiver design for RIS is proposed.

3.1 AI-based algorithm design

With the powerful learning capability and convenient implementation relying on parallel architectures, AI can also be used to speed up the process of an algorithm. We will present the methodology for RIS-aided wireless communications using several typical transmission techniques, including channel estimation, precoding, and beam training.

3.1.1 Channel estimation

The channel estimation in RIS-aided wireless communication systems will meet greater obstacles than the traditional systems. Fortunately, these obstacles can be elegantly solved by AI methods.

Firstly, one of the most serious obstacles is the unaffordable pilot overhead to estimate the high-dimensional channel. To be specific, most existing channel estimation algorithms only estimate the BS-RIS-UE cascaded channel [5, 6], whose pilot overhead is proportional to the number of RIS elements. Therefore, due to a large number of RIS elements, the pilot overhead to estimate the channel can be prohibitively high in practice. To address this issue, authors of [7] utilize a fraction of all RIS elements and obtain the partial channel among the BS, the UEs, and the chosen RIS elements, and then to reconstruct the complete channel among the BS, the UEs, and all RIS elements. Specifically, instead of using one CNN directly, inspired by the Ordinary Differential Equation (ODE), an ODE CNN-based framework is proposed to extrapolate the channels from those estimated at chosen RIS elements, where the partial channel is the input and the complete channel is the output. As for the simulation results, the proposed CNN-based scheme can effectively compress the high-dimensional RIS channel and obtain accurate solutions.

Furthermore, an AI-based channel estimation method is considered to solve the beam split effect in wideband RIS systems [8]. As the beam split effect could cause the different subcarriers to transmit to different physical directions, a serious channel estimation performance loss will be incurred regarding the same physical directions across the entire bandwidth. To estimate the frequency-selective cascaded channel for RIS systems, authors of [8] proposed two De-noising CNNs (DnCNNs) to extract the double-structured sparsity features [9]. Specifically, the row-structured and column-structured features are detected by jointly exploiting multiple subcarriers, respectively. Then, the RIS cascaded channel is reconstructed according to the extracted double-structured features. Finally, apart from the advantages in reducing pilot over-head and solving the beam split effect by AI, several pieces of work also utilize the AI method to improve estimation accuracy [10, 11]. For example, based on the noisy image acquired by least square method, a De-noising CNN (DnCNN)-based method is proposed to improve channel estimation accuracy [10].

3.1.2 Precoding

Precoding makes the signals propagate toward certain directions instead of radiating around, which can improve the spectral efficiency, expand the coverage area and reduce interference. Therefore, in RIS-aided communications, precoding is a key technique to fully exploit the advantages of the RIS. By designing the configuration of the RIS, the beam can be adjusted to transmit signals in a specific direction. In particular, numerous joint precoding techniques with different design goals are proposed to improve the system performance of RIS-aided communications. However, as mentioned before, the passive RIS with discrete phase shifts is preferred in practice, which results in a non-convex RIS precoding optimization problem. It is hard to figure out the closed-form solution to this non-convex RIS precoding design problem. In this case, iterative search schemes are often utilized to solve this non-convex problem, which still suffers from high complexity because the RIS aperture is usually large as mentioned before. Fortunately, by improving the precoding design module with AI, RIS can directly generate the beams re-quired by the users with less time complexity. The AI-based precoding methods can be divided into two categories as follows.

Firstly, most of the existing works on AI-based precoding uses the the neural network to approximate a traditional algorithm to reduce the computational complexity. For example, in [12], an AI-empowered RIS is designed and fabricated. Specifically, the CNN is applied to train the RIS precoding matrix with the radiation pattern, including the upper mask, lower mask, and direction information of

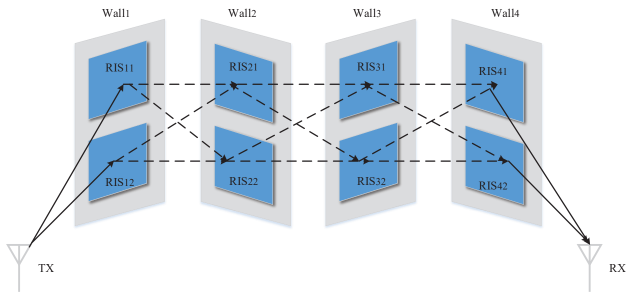

Fig. 2 – Conceptual representation of programmable wireless environments as a neural network

the desired beam. Based on these beam requirements of the user, the trained model can directly realize real-time RIS beam-forming. Simulation results demonstrate that AI-based precoding design can improve performance and reduce the time complexity compared with the conventional design methods like particle swarm optimization. Additionally, in [13], the problem of RIS optimal precoding design is transformed into a classification problem. Inspired by the superior performance of machine learning in solving non-convex classification problems, a deep neural network is employed to predict the phase-shifting classification result of each RIS element and reduce the computational complexity significantly. These two pieces of work train the neural network to dig a mapping relationship between the inputs and the RIS configuration in the offline stage from a big training dataset, which is utilized to provide a good generalization ability. Then in the online stage, with the help of the trained networks, accurate predictions can be made from the inputs at a fast speed. It is the tradeoff between the time and data-consuming offline training and real-time utilization.

Secondly, instead of using a neural network to approximate a traditional algorithm, a method, where an interpretable neural network aims at modeling wireless propagation is proposed to design RIS configuration based on the process of DNN training [14]. As shown in Fig. 2, the wireless propagation of the RIS-aided system is modeled as a DNN, where the walls are considered as layers of DNN and tiles as nodes of DNN. Concretely, the input is featured by propagation environments, for example, the numbers and locations of Txs and Rxs and operating frequencies. The corresponding output is the received power at Rx. During the training period, the DNN learns the wireless propagation environments and the output of the DNN is becoming closer to the expected received power. After training completes, the RIS configuration is also obtained to facilitate the users.

Both AI-based precoding methods utilize AI to avoid the iterative optimization algorithm with high computational complexity. However, the second method is more flexible, since it can realize different user requirements only if you change the output label of DNN as the expected requirements. Furthermore, a joint channel estimation and beam-forming method based on AI is proposed to avoid a large channel estimation overhead and a difficult high-dimensional passive beam-forming design problem [15]. The key idea of this paper is to parameterize the neural network to realize the direct mapping from the observing pilots to the RIS beam-forming configuration. By eliminating the explicit RIS cascaded channel estimation, the proposed joint channel estimation and beam-forming method could realize higher sum-rate performance, especially in the limited pilot condition.

3.1.3 Beam training

As mentioned before, as the operating frequency increases, the direct BS-UEs links become more vulnerable due to the severe blockage and propagation loss. An RIS can provide additional virtual links, and enhance the signal power by implementing efficient precoding. However, full or even partial knowledge of the channel state information at the transceivers is difficult to obtain during the initial access process. Therefore, the passive beam training at the RIS and the beam training at the BS should be executed before data transmission, aiming at finding the optimal spatial path that maximizes the received power at UEs. In order to cover the target area with the pencil-like sharp beams, beam training requires a large number of directional codewords in the beam training codebook. Moreover, the overhead of beam training in RIS-aided communications is determined by the product of the number of codewords in the beam training codebook at BS and that of RIS. Thus, beam training in RIS-aided communications is practically challenging due to the massive number of RIS elements. Therefore, in RIS-aided communications, the conventional beam training methods, for example, exhaustive search in codebook will lead to an excessively high training overhead.

To solve this problem, a Deep Reinforcement Learning (DRL) framework is proposed to predict the RIS codeword from the predefined codebook with minimal beam training overhead in [16]. In the proposed DRL framework, some elements on the RIS are equipped with active channel sensors. These active elements can both estimate the channel and reflect the incident signal by applying a tuned phase shift, while the passive elements on the RIS are only reflectors. With the ability to estimate the channel, RIS is adopted as an RL agent to acquire the current state and reward from the environment (i.e., various scatterers and user locations), which is constructed as the multipath signature. The multipath signature will be utilized to generate the training samples in RL agent interaction and RL agent training. Specifically, the deep Q-network is trained to map an input state (the multipath signature) to an output action (codeword of RIS reflection coefficients). Compared to the Supervised Deep Learning (SL) solution, the proposed DRL solution can approach the optimal rate with almost no more than one percent of the beams operated by the SL method in the training phase.

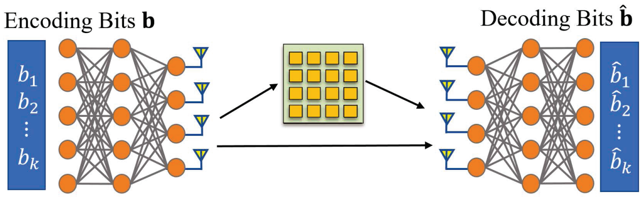

Fig. 3 – The architecture of the DNN-assisted transceiver design

3.2 AI-based architecture design

In this subsection, we focus on AI-based architecture design for RIS-aided communications. By AI-based joint transceiver design, the performance of RIS-aided communications can be improved. Following the logical order, we first introduce the DNN-assisted transceiver design and then present the more revolutionary DNN-like joint transceiver design. In particular, DNN-assisted design includes classical DNN for jointly optimizing transceivers, which shows a performance gain in terms of the Bit Error Rate (BER). By contrast, DNN-like transceiver design does not include classical DNN, and the design of RIS-aided communications is realized by the training of DNN.

3.2.1 DNN-assisted transceiver design

As mentioned before, RIS can manipulate the wireless channel with nearly passive elements, it is an energy-efficient way to improve the quality of the received signals through a carefully designed RIS precoding matrix. However, an RIS has a large number of elements, and it is difficult to obtain the closed-form solution of a precoding vector at the BS and precoding matrix at the RIS. Most of the existing works iteratively optimizes the precoding at the BS, the passive beam-forming at the RIS, and the combiner at the user. However, utilizing the iterative optimization algorithm may converge to a local optimum. To address this problem, as shown in Fig. 3, a DNN-assisted transceiver design is proposed [17] to directly optimize the BER performance in RIS-assisted MIMO downlink communications, where the whole AI-based communication system including baseband processing is jointly optimized. Specifically, in this structure, the BS and UE are equipped with DNNs to process the signal, and an RIS is used as the relay. The DNN at the BS aims at encoding bits and generating the transmitted signal. Then the RIS reflects the incident transmitted signal and configures it by tuning its phase, which is represented by the precoding matrix. Finally, the DNN at the UE decodes the received signals into predicted bits. The passive precoding matrix at RIS and the DNNs at the BS and the UE are jointly optimized.

Specifically, the passive precoding matrix at RIS and the parameters of DNNs at the BS and the UE are trained by minimizing the loss function, which is the cross-entropy of input encoding bits $\boldsymbol{b}$ and output decoding bits $\hat{\boldsymbol{b}}$ under the power constraint and constant norm constraint. Next, for this optimization problem, a BP

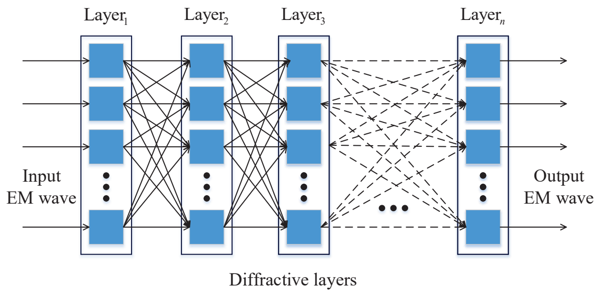

Fig. 4 – Diffractive deep neural networks [25]

algorithm is used to optimize the system parameters until the loss converges. At last, the optimized parameters are actually deployed at the BS, RIS, and UE.

3.2.2 *DNN-like transceiver design*

Despite the application in wireless communications, the implementation of DNN in practice also draws a lot of attention. In [18], rather than using the traditional computer platforms to implement DNNs, the optical platform (also called diffractive deep neural networks, D^2NN) could realize DNN with diffractive surfaces. Specifically, as shown in Fig. 4, the diffractive surfaces can be considered as the layers of the DNN, where each element on a given layer represents a neuron that is connected to other neurons of the next layer through optical diffraction. Each element either transmits or reflects the input wave, which acts as the secondary wave source. The characteristics of the secondary wave, such as phase, are determined reflection coefficient at those elements. These reflection coefficients of each point or neuron are learnable diffractive network parameters that are iteratively adjusted during the training process. After an extensive training phase, the diffractive network parameters of D^2NN are fixed and the reflection coefficients of the neurons of all layers are settled. The D^2NN takes advantage of the property that light waves propagate at the speed of light. Therefore, this work may bring a potentially elegant solution to some communication problems with the high demand of timeliness, for example, the transmission on the Internet of Vehicles (IoV). However, the proposed D^2NN in [18] has fixed DNN architecture once fabricated, thus it has the poor ability of generalization and cannot be re-used for other scenarios.

To solve this problem, an on-site Programmable Artificial Intelligence Machine (PAIM) is proposed in [19]. Instead of using diffractive surfaces, RISs act as the programmable physical layers of D^2NN and can be utilized for wireless communications. Specifically, the elements controlled by FPGA on RISs can be regarded as the basis to construct the reprogrammable physical layers of D^2NN. With the programmable elements on RIS, PAIM can execute various tasks including mobile communication encoder-decoder, and real-time multibeam focusing via a multi-layer digital-coding RIS array.

Furthermore, a novel wireless transceiver based on the RIS neural network structure PAIM can be constructed [20], which can process the signal without energy-hungry RF modules compared to the traditional transceiver. In this architecture, all the traditional signal processing is completed through the RIS array. Each RIS (known as the layer of DNN) is composed of multiple elements (known as the neurons), which are interconnected via EM wave propagation. The responses of RIS to EM waves can be changed with different external control signals in specific tasks. As mentioned before, due to the ability of PAIM to transmit waves at the speed of light, the PAIM-based transceiver can handle the real-time signal processing task.

3.3 Interplay between AI and RIS

From the discussion above, we can find that despite the significant differences between wireless AI and RIS, we focus on their profound interplay to circumvent their weaknesses.
On the one hand, with great learning ability, AI can promote the deployment of RIS in practice. In particular, AI can contribute to reducing the unaffordable overhead, including the pilot overhead in channel estimation and the training overhead in beam training. Moreover, relying on parallel architectures with convenient implementation, the process of the algorithm can be accelerated, such as the AI-based precoding design in RIS-aided communications. On the other hand, the research on RIS also helps AI to develop. Specifically, as DNN can be implemented by the RIS, the DNN can operate at the speed of light. For specific problems or functions, by leveraging the RIS, we can design some specialized RIS-based DNNs for specific problems with guaranteed performance.

4. CHALLENGES AND RESEARCH OPPORTUNITIES

As mentioned above, the previous section presents encouraging advantages of AI-based designs for RIS-aided communications. However, AI-based designs are still at an early stage, and there remains many challenges for further study. In this section, we present five key challenges in this area, and the research opportunities will also be discussed.

4.1 AI for near-field RIS beam training

As mentioned before, an RIS with a large number of reconfigurable elements will have an enlarged array aperture. With the increase of the RIS aperture, the fundamental EM field property may change. The EM field has two categories, i.e., the far-field region and the near-field region. The boundary between these two regions is the Rayleigh distance [21], which is proportional to the square of the array aperture. Thus, as the number of RIS elements dramatically increase, the near-field range will expand. For example, if an RIS with 256 elements is working at 100 GHz, the radius of the near-field region is about 100 m. Thus, the user will be in the near field with a high probability. However, the traditional beam training schemes designed for a far-field scenario is not suitable for a near-field scenario. Specifically, when the BS or the UE is in the near-field region of the RIS, the EM wave arriving at different RIS elements has different incident angles and transmission distances. Therefore, the beam training codebook needs to cover not only all the possible angles but also all the different transmission distances, which results in prohibitive beam training overhead. In this case, the AI algorithm can be considered as one solution to reducing the beam training overhead.

4.2 AI for active RIS

Due to the "multiplicative fading" effect of an RIS, which means the BS-RIS-UE link will experience fading twice, the received power at the UE is usually weak. In this case, thousands or even more elements are required to compensate for the very serious attenuation of the BS-RIS-UE link, which will bring a lot of pressure to signal processing for RIS-aided communications, for example, channel estimation with an unaffordable overhead. To mitigate the "multiplicative fading" effect, an active RIS is proposed in [22], where the active RIS amplifies and reflects the incident signal with a power amplifier. In this new structure, the amplification matrix of the active RIS is required to design and the noise affected by the reflection-type amplifier should be considered. Therefore, the techniques mentioned previously like the channel estimation need to be re-designed for the active RIS. Some AI algorithms mentioned previously can be adjusted to solve the challenges in active RIS-aided communications.

4.3 AI for RIS-aided cell-free systems

A cell-free network is considered as a promising solution to address inter-cell interference, which improves the network capacity for the future communication systems. Unlike the classical cellular network, in a cell-free network, all BSs without cell boundaries jointly serve all users cooperatively. To improve the cell-free network capacity further, an RIS can be utilized as an alternative to the BS to further enhance the capacity with low cost and energy consumption [23]. However, due to a large number of BSs and RISs in the cell-free networks, the complexity increases sharply in the joint precoding design problem and channel estimation problem at the BSs and RISs. An AI method is a potential way to reduce the signal processing complexity in an RIS-aided cell-free system.

4.4 Generalization

Although AI schemes show great efficiency for the existing wireless communication systems, they still suffer from the generalization ability due to the next three reasons. First of all, large amounts of data are usually unavailable due to the passive elements of the RIS, which leads to the overfitting problem. Therefore, the trained AI model only performs well on the training dataset. Then, a lot of AI models are trained under a fixed SNR and act well under this specific SNR, which is unrealistic in the practical communication system. Moreover, many AI models are application-specific because AI techniques may extract different channel features for different application scenarios.

4.5 Implementation

Apart from the challenges listed above, the implementation of AI-based methods in practical communication systems is also a challenge. First, since most of the AI methods are data-driven and the training overhead is unacceptable, an additional structure such as a cloud server should be deployed based on the existing infrastructure. Second, for the AI-based architecture design, the whole RIS-based communication infrastructure is totally different from the traditional infrastructure equipped with a radio frequency chain and signal processing functionality. As the AI-based architecture design may not replace the traditional infrastructure completely in a short time, a switching scheme is required to switch the AI-based methods and the traditional methods.

5. CONCLUSIONS

In this paper, we have discussed two pairs of dominant methodologies for the applications of AI in RIS-aided wireless communications, namely AI-based algorithm design and architecture design. We have started with the current challenges in RIS-aided wireless communications, and then demonstrated the specific AI methods to address those challenges. We have also analyzed their design principles, key features, and advantages to show that AI is capable of reducing the overhead and computational complexity, and also of changing the classical architecture for wireless communications. In addition to the discussions above, there are still some challenges and research opportunities in this emerging area, such as the AI for near-field beam training. We believe that AI can offer a good solution to some important challenges of RIS-aided wireless communications, and the interplay between AI and RIS can further make the RIS-controlled environments more intelligent.

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