A Survey of Deep Learning Architectures for Intelligent Reflecting Surfaces
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Abstract—Intelligent reflecting surfaces (IRSs) have recently received significant attention for wireless communications because it reduces the hardware complexity, physical size, weight, and cost of conventional large arrays. However, deployment of IRS entails dealing with multiple channel links between the base station (BS) and the users. Further, the BS and IRS beamformers require a joint design, wherein the IRS elements must be rapidly reconfigured. Data-driven techniques, such as deep learning (DL), are critical in addressing these challenges. The lower computation time and model-free nature of DL makes it robust against the data imperfections and environmental changes. At the physical layer, DL has been shown to be effective for IRS signal detection, channel estimation and active/passive beamforming using architectures such as supervised, unsupervised and reinforcement learning. This article provides a synopsis of these techniques for designing DL-based IRS-assisted wireless systems.

I. INTRODUCTION

The next-generation millimeter wave (mm-Wave) massive multiple-input multiple-output (MIMO) systems require large antenna arrays with a dedicated radio-frequency (RF) chain for each antenna. This results in expensive and large system architectures which consume high power and processing resources. To reduce the number of RF chains while also maintaining sufficient beamforming gains, hybrid analog and digital beamforming architectures were introduced. However, the resulting cost and energy overheads using these systems remain a concern. Recently, intelligent reflective surfaces (IRSs) have emerged as a feasible solution to implement a low cost and light-weight alternative to large arrays complexity in both outdoor and indoor applications, usually with separate operating frequencies or spectral bands. (Fig. 1).

An IRS is an electromagnetic two-dimensional surface that is composed of large number of passive reconfigurable meta-material elements, which reflect the incoming signal by introducing a pre-determined phase shift. This phase shift is controlled via external signals by the base station (BS) through a backhaul control link. As a result, the incoming signal from the BS can be manipulated in real-time, thereby, reflecting the received signal toward the users. Hence, the usage of IRS enhances the signal energy received by distant users and expands the coverage of the BS. It is, therefore, required to jointly design the beamformer parameters both at the IRS and BS. This achieves desired channel conditions, wherein the BS conveys the information to multiple users through the IRS [2]. Different from amplify-and-forward (AF) relay systems, an IRS can have both active and passive components, which can provide a flexible configuration, thus, it has less active transmit modules or totally reflects the received signal as a passive surface. Thus, the IRS is much more energy- and spectrum-efficient [3].

The accuracy of beamformer design strongly relies on the knowledge of the channel information. In fact, the IRS-assisted systems include multiple communications links, i.e., a direct channel from BS to users and a cascaded channel from BS to users through IRS. This makes the IRS scenario even more challenging than the conventional massive MIMO systems. Furthermore, the wireless channel is dynamic and uncertain because of changing IRS configurations. Consequently, there exists an inherit uncertainty stemming from the IRS configuration and the channel dynamics. These characteristics of IRS make the system design very challenging [2] [3].

To address the aforementioned uncertainties and nonlinearities imposed by channel equalization, hardware impairments, and sub-optimality of high-dimensional problems, model-free techniques have become common in wireless communications [15]. In this context, deep learning (DL) is particularly powerful in extracting the features from the raw data and providing a “meaning” to the input by constructing a model-free data mapping with huge number of learnable parameters. Furthermore, DL is helpful when modeling the channel characteristics thanks to its data-driven structure. As listed below, DL is more efficient than model-based techniques that largely rely on mathematical models:

- A learning model constructs a non-linear mapping between the raw input data and the desired output to approximate a problem from a model-free perspective [15]. Thus, its prediction performance is robust against the corruptions/imperfections in the wireless channel data.
- DL learns the feature patterns, which are easily updated for the new data and adapted to environmental changes. In the long run, this results in in lower computational complexity than a model-based optimization [2].
- DL-based solutions have significantly reduced run-times because of parallel processing capabilities. On the other hand, it is not straightforward to achieve parallel implementations of conventional optimization and signal processing algorithms [7].

The aforementioned advantages have led to DL superseding the optimization-based techniques in the system design for
Fig. 1. IRS-assisted wireless communications for outdoor and indoor deployments. A BS on top of the infrastructure (left) communicates with the users on ground through an intermediate IRS mounted on other buildings (center). The BS also serves users (right) inside the apartment building through an IRS placed on the wall of the room.

| Scheme | NN Architecture | Benefits | Drawbacks |
|--------|-----------------|----------|-----------|
| **Signal detection** | | | |
| SL [5] | MLP with 3 layers | No need for channel estimation algorithm | Still needs to design beamformers and requires huge datasets and deeper NN architectures |
| RL [6] | Twin CNNs with 3 convolutional, 3 fully connected layers | Each user estimates its own channel with the trained model | Data collection requires channel training by turning on/off each IRS elements |
| FL [7] | A single CNN with 3 convolutional, 3 fully connected layers | Less transmission overhead for training. A single CNN estimates both cascaded and direct channels | Performance depends on the number of users and the diversity of the local datasets |
| SL [8] | DDNN with 15 convolutional layers | Leverages both compressed sensing (CS) and DL methods | Requires active IRS elements. High prediction complexity arising from CS algorithms |
| **Beamforming** | | | |
| SL [9] | MLP with 4 layers | Reduced pilot training overhead | Requires active IRS elements for channel training |
| UL [10] | MLP with 5 layers | Reduced complexity at the model training stage | Implicitly needs the reflect beamformers as labels |
| RL [11] | DQN with 4 layers | Provides standalone operation since RL does not require labels like SL | Longer training. Active IRS elements needed for channel acquisition |
| RL [12] | DDPG with 4-layered actor and critic networks | Better performance than DQN | Large number of NN parameters are involved |
| FL [13] | DDPG with actor and critic networks | Accelerated learning performance with the aid of optimization, shrinking the search space | Additional optimization tools needed |
| **Secure beamforming** | | | |
| RL [14] | DQN with 3 layers | Less transmission overhead during model training | IRS must be connected to the PS |
| **Energy-efficient beamforming** | | | |
| RL [15] | DQN | Energy-efficient and robust against uncertainties | IRS beamforming only |
| **Indoor beamforming** | | | |
| SL [16] | MLP with 5 layers | Reduces hardware complexity of multiple BSs and improves RSS for indoor environments | Learning model performance relies on room conditions |

Lately, the IRS-aided wireless systems have exploited DL to handle very challenging problems. For instance, signal detection in IRS requires development of end-to-end learning systems under the effect of channel and beamformers [5]. The channel needs to be estimated for multiple communication links, i.e., BS-user and BS-IRS-user [6]. Finally, beamformers are designed (by solving complex optimization problems) for phase shifters at both BS and passive elements of the IRS [9]. The DL-based techniques are able to handle the multidimensional, huge datasets in all these problems and may also be employed for channel modeling [1], where the conventional model-based approaches are not very useful. There have been recent surveys on applying DL [15] and IRS [1] individually to wireless communications. In this article, we provide an overview of systems which jointly employ both approaches. In particular, we describe DL techniques (Table I) for three main IRS problems: signal detection, channel estimation, and beamforming. Each of these requires different DL architectures, which have so far included supervised learning (SL), unsupervised learning (UL), reinforcement learning (RL) and federated learning (FL). The UL and RL do not require labeling; SL needs labeled dataset; and FL has distributed structure for model training. We provide a detailed synopsis...
Fig. 2. Model-based versus learning-based frameworks for signal detection and channel estimation. Model-based approach (top) comprises multiple subsystems to process the received signal. Learning-based signal detection (bottom, left) provides an end-to-end data mapping from the corrupted symbols under the channel effects at the receiver to the transmit symbols. Learning-based channel estimation (bottom, right) maps the input received signals to the channel estimate as output labels.

II. DL-BASED SIGNAL DETECTION IN IRS

The signal detection comprises mapping the received symbols under the effect of channel and beamformers to transmit symbols (Fig. 2). To leverage DL for signal detection, [5] devised a multi-layer perceptron (MLP) for mapping the channel and reflecting beamformer effected data symbols to the transmit symbols. The MLP is a feedforward neural network (NN) composed of multiple hidden layers. The framework in [5] uses three fully connected layers. Once the MLP is trained on a dataset composed of received-transmitted data symbols for Rayleigh fading channels, each user feeds the learning model with the block of received symbols. These blocks account for the effect of channel and beamformers. Then, MLP yields the estimated transmit symbols.

A major advantage of this approach is its simplicity that the learning model estimates the data symbols directly, without a prior stage for channel estimation. Thus, this method is helpful reducing the cost of channel acquisition. However, a few challenges remain to achieve a reliable performance. The training data should be collected under several channel conditions and different beamformer configurations so that the trained model learns the environment well and reflects the accurate performance in different scenarios. This is a particularly challenging task because it requires collection of the training data for different user locations.

Lessons Learned: DL-based signal detection is helpful for bypassing the channel estimation stage. However, this may require huge training datasets collected under different channel conditions. An alternative is to consider estimating the wireless channel via DL, as discussed in the next section.

III. DL-BASED IRS CHANNEL ESTIMATION

The IRS is composed of a huge number of reflecting elements and, therefore, channel state acquisition is a major task in IRS-assisted wireless systems. A common approach is to turn on and off each individual IRS element one-by-one while also using orthogonal pilot signals to estimate the channel between the BS and the users through IRS. In particular, IRS channel estimation via DL involves constructing a mapping between the received input signals at the user and the channel information of direct and cascaded links (Fig. 2). In this way, DL-based techniques reduce the pilot percentage and complexity in channel estimation stage [7].

The SL approach proposed in [6] estimates both direct and cascaded channels via twin convolutional neural networks (CNNs). First, the received pilot signals at the user are collected by sequentially turning on the individual IRS elements. Then, the collected data are used to find the least squares (LS) estimate of the cascaded and the direct channels. Both CNNs are trained to map the LS channel estimates to the true channel data. The upshot is that each user estimates its own channels only once and feeds the received pilot data (LS estimate) to the trained CNN models. The CNNs have higher tolerance than MLP against the channel data uncertainties, imperfections (such as switching mismatch) of IRS elements.

When the model training is conducted at the user with huge datasets as in [6] for various channel/user/configurations, the
system may lack sufficient computational capability. This is overcome by FL-based training [7], where the learning model updates are computed at the devices (nodes) and aggregated at the BS (central server) (Fig. 3), thereby eliminating the transmission of raw data. FL significantly reduces the transmission overhead since the size of the datasets is usually larger than the size of the learning model, and its performance improves as the number of users increases [7] [13]. Furthermore, instead of using two CNNs demanding two datasets as in [6], a single CNN in [7] jointly estimates both cascaded and direct channels.

Although FL reduces the transmission overhead during model training, its training performance is upper bounded by the centralized model training, i.e., training the model with the whole dataset at once. Therefore, the prediction performance of FL is usually poorer than the centralized learning (CL). As shown in Fig. 3, CL and FL frameworks are compared with the minimum mean-squared-error (MMSE) and the LS estimation. We note that FL performs slightly poorer than CL in high SNR regimes. Despite this, FL significantly reduces the transmission overhead, e.g., approximately ten-fold reduction in the number transmitted symbols [7].

Both SL- and FL-based channel estimation techniques suffer from high channel training overhead. In this context, compressive channel estimation with deep denoising neural networks (DDNNs) is very effective [8]. It employs a hybrid passive/active IRS architecture, where the active IRS elements are used for uplink pilot training and passive ones for reflecting the signal from the BS to the users. Once the BS collects the compressed received pilot measurements, complete channel matrix is recovered through sparse reconstruction algorithms such as orthogonal matching pursuit (OMP). Then, DDNN is used to improve the channel estimation accuracy by exploiting the correlation between the real and imaginary parts of the mm-Wave channel in angular-delay domain. During training, the input is the OMP-reconstructed channel matrix and the output is the noise, i.e., the difference between the OMP estimate and the ground truth channel data. This method leverages both CS and DL yielding a performance better than using these techniques individually. The major drawback is the additional hardware complexity introduced by the active IRS elements.

Lessons Learned: The additional OMP stage in DDNN aids in achieving lower MSE than the DDNN-only architectures. Challenges in CL-based channel estimation arise from large dataset transmission and could be mitigated via FL. As discussed next, after estimating the IRS channel, the next task is to configure the IRS beamformers.

IV. DL-AIDED BEAMFORMING FOR IRS APPLICATIONS

A. Beamforming at the IRS

The IRS beamforming requires passive elements continuously to reliably reflect the BS signal to the users. Here, the MLP architecture [9] is helpful in designing the reflect beamforming weights using active IRS elements [8]. These elements are randomly distributed through the IRS. They are used for pilot training, after which compressed channel estimation is carried out using OMP. In order to collect the dataset, the reflect beamforming weights are optimized by using the estimated channel data. Finally, a training dataset is constructed with channel data and reflect beamformers as the input-output pairs for an SL framework. Note that the active IRS elements present similar shortcomings as in [8]. However, the method in [9] excels by leveraging DL for designing beamformers.

The labeling process in [9] demands solving an optimization problem for each channel instance in training data generation stage. One possible way to mitigate this is to use label-free techniques, such as UL. The UL approach in [10] for reflect beamforming design employs MLP with five fully connected layers. The network maps the vectorized cascaded and direct channel data input to the output comprising the phase values of the reflect beamformers. The loss function is selected as the negative of the norm of the channel vector, which may seem like an unsupervised approach because it does not minimize the error between the label and learning model prediction. However, this technique yields the phase information at the output uniquely for each training samples. Consequently, the beamformers implicitly behave like a label in the training process. In [10], the output of the NN is a design parameter, i.e., reflect beamformer phases, which have the complexity of beamformer optimization for each input.

In order to eliminate the expensive labeling process of the SL-based techniques, [11] employed RL to design the reflect beamformers for single-antenna users and BS. The RL is a promising approach which directly yields the output by optimizing the objective function of the learning model. First, the channel state is estimated by using two orthogonal pilot signals. An action vector is selected either by exploitation (using prior experience of the learning model) or exploration (using a predefined codebook). After computing the achievable rate based on the selected action vector from the environment, a reward or penalty is imposed by comparing with the

![Fig. 3. The mean-squared-error of channel estimates normalized against ground truth channel, obtained using CNN in centralized and federated learning frameworks, MMSE and LS. The BS consisted of 64 antennas and IRS employed 64 passive reflecting elements.]
achievable rate with a threshold. Upon reward calculation, a Deep Quality Network (DQN) (Fig. 5) updates the map from the input state (channel data) to the output action (action vector composed of reflect beamformer weights). The training data is generated in an electromagnetic (EM) simulation tool, and this process is repeated for several input states until the learning model converges. While RL is not an IRS-specific technique, it is particularly useful in lowering the overhead of labeling process as compared to SL architectures deployed by RNN or CNN models, which require labeled datasets. The RL algorithm learns reflect beamformer weights based on the optimization of the achievable rate. Thus, RL presents a solution for online learning schemes, where the model effectively adapts to the changes in the propagation environment. However, RL techniques have longer training times than the SL approaches because reward mechanism and discrete action spaces make it difficult to reach the global optimum. The label-free process implies that the RL usually has slightly poorer performance than the SL.

To accelerate the training stage by the use of continuous action spaces, a deep deterministic policy gradient (DDPG) (Fig. 5) was introduced in [2]. Here, actor-critic network architectures are used to compute actions and target values, respectively. First, the learning stage is initialized by the use of input state excited by cascaded and direct channels. Given the state information, a deep policy network (DPN) (actor) constructs the actions (reflection beamformer phases). Here, the DPN provides a continuous action space that converges faster than the DQN architecture in [11]. The action vector is used by the critic network architecture to estimate the received signal-to-noise-ratio (SNR) as objective. This SNR then yields the target beamformer vector under the learning policy. Using the gradient of DPN, the network parameters are updated and the next state is constructed as the combination of the received SNR and the reflecting beamformers.

Even if RL is a label-free approach that reduces the overhead during training data generation, training approaches in [2] [11] [12] demand expensive transmission overhead to be trained on huge datasets. This is mitigated in FL techniques. The FL approach in [13] learns the IRS reflect beamformers by training an MLP by computing the model updates at each user with the local dataset. The model updates are aggregated in a parameter server (PS), which is connected to the IRS. The MLP input is the cascaded channel information and the output labels are IRS beamformer weights. The federated architecture lowers the transmission overhead during training. However, it is assumed that the PS is connected to the IRS. The simple architecture of the IRS could make this infeasible. It is more practical to access the PS via BS for model training.

B. Secure-Beamforming

Physical layer security in wireless systems is largely achieved through signal processing techniques, such as cooperative relaying and cooperative jamming. The hardware complexity is a major issue in these methods. The low-cost, less complex IRS-based systems have the potential to mitigate these problems. The RL-based secure beamforming [14] minimizes the secrecy rate by jointly designing the beamformers at the IRS and BS to serve multiple legitimate users in the presence of eavesdroppers. The RL algorithm accepts the states as the channel information of all users, secrecy rate and transmission rate. Similar to [2], the action vector is beamformers at the BS and IRS. The reward function is designed based on the secrecy rate of users. A DQN is trained to learn the beamformers by minimizing the secrecy rate while guaranteeing the quality-of-service requirements. The model training takes place at the BS, which is responsible for collecting the environment information (channel data) and making decisions for secure beamforming. This scheme is more realistic and reliable than that of [2] [11], which ignore the effect of eavesdroppers. The learning model includes high-dimensional state and action information, such as the channels of all users and beamformers of BS and IRS. This may necessitate more computing resources for training than non-secure IRS [2] [11] and conventional SL techniques [6] [9].

C. Energy-Efficient Beamforming

The IRS configuration dynamically changes depending on the network status. It is very demanding for the BS to optimize the transmit power every time when the on/off status of IRS elements is updated. This could be addressed by accounting energy-efficiency in the beamformer design problem. In [4], a self-powered IRS scenario maximizes the energy-efficiency by optimizing the transmit power and the IRS beamformer phases. In this DQN-based RL approach, the BS learns the outcome of the system performance while updating the model parameters. Thus, the BS makes decisions to allocate the radio resources by relying on only the estimated channel information. The dataset for the RL framework has states selected as the estimated channels from users and the energy level of the IRS. Meanwhile, the action vector includes the transmit power, the IRS beamformer phases and on/off status of the IRS elements. The learning policy is based on the reward which is selected as the energy-efficiency of the overall system. However, this work considers only IRS beamforming and ignores the same at the BS.
detection, channel estimation, and beamformer design. Based techniques for all wireless communications tasks: signal

A. DL-Related Challenges

The need for massive data collection and subsequent training is a bottleneck in successful implementation of DL-based techniques for all wireless communications tasks: signal detection, channel estimation, and beamformer design.

1) Data collection: The signal detection requires collection and storage of transmit and receive data symbols for different channel conditions, e.g., user location/angles and modulation types [5]. The prerequisites for channel estimation and beamforming are even more tedious because of additional labeling process. This is difficult to overcome in, especially online scenarios. Apart from SL, the label-free structure in RL is particularly helpful but at the cost of training times. It is possible to relax the data collection requirements by realizing the propagation environment in a numerical EM simulation tool [9, 11] and then using a more realistically simulated data. This is helpful in constructing the training dataset offline but chances of failure remain in a real world scenario. Very recently, public datasets for channel estimation problem in IRS-aided communications were made available in the 2021 IEEE Signal Processing Cup competition.

2) Model training: The models are usually trained offline prior to their online deployment at a PS connected to the BS. In addition, the model training complexity increases with the number of IRS elements and IRSs deployed between the users and the BS. Some experimental studies include IRS with 10000 elements operating at 10.5 GHz [1]. Hence, huge transmission overhead is introduced for model training. The FL has potential to reduce this cost and enable a communication-efficient model training (see, e.g., Fig. 3). Here, combining the label-free structure of RL and the communications efficiency of FL, i.e., federated reinforcement learning, could be the next step.

3) Environment adaptation and robustness: The behavior of the channel affects all DL-based tasks including channel estimation, beamforming, user scheduling, power allocation, and antenna selection/switching. Addressing the trade-off between the bias and the variance of the model output is essential for robust performance. This is usually achieved through data validation so that the learning model does not either over-fit or under-fit the training data. Nonetheless, this does not generalize the learning performance to different environments. Moreover, the current DL architectures for wireless systems remain environment-specific because the input data space of their learning model is limited. As a result, the performance degrades significantly when the learning model is fed with the input from unlearned/uncovered data space. In order to cover larger data spaces and provide a robust performance against the changes in the environment, wider and deeper learning models are required. But the current DL architectures for wireless communications comprise less than a million neurons and are composed of only a few layers (Table 1) [7]. Therefore, wider and deeper designs are of great interest for future DL-based IRS-aided systems.

B. IRS-Related Challenges

Specific implementation challenges have also been identified within emerging technologies, some of which we elaborate here.

1) Cell-free (CF) networks: These architectures yield reduced average path loss, some degree of channel hardening and improved inter-cell interference over the conventional massive MIMO systems. In this context, DL-aided IRS beamforming has the potential to improve the network capacity and energy-efficiency. The robustness of such a system may be improved by designing scalable network and long-term passive beamformers.
2) THz implementation: Compared to mm-Wave, the propagation loss is more significant in THz bands thereby leading to shorter ranges. While mm-Wave channel model is based on a single line-of-sight (LoS) path with several non-LoS paths, the THz channel is largely a superposition of multiple LoS paths. Here, DL-aided IRS helps in extending the BS coverage. However, implementation of THz-band IRS remains a challenge from the device perspective. In recent work, the introduction of hot stamping in fabricating IRS offers improvement in addressing the beam squint and wide beam misalignment phenomena specific to THz.

3) Integrated sensing and communications: Recent research in ISAC envisions spectrum-sharing radar and communications in a hardware- and energy-efficient paradigm. Here, again, IRS has been shown to allow range extension, NLoS sensing/communications, improved interference suppression and enhanced security. DL-aided techniques have been identified for joint processing, multi-hop channel acquisition, and reduced post-training complexity for various ISAC tasks.

VI. SUMMARY AND FUTURE OUTLOOK

We surveyed DL architectures of IRS-assisted wireless systems for key applications, including signal detection, channel estimation, and beamforming. We extensively discussed various learning architectures, such as SL, UL, FL and RL and their IRS-specific considerations. The advantages of DL-based IRS systems lie in reduced complexity and better robustness, as enunciated below.

- Whereas the label-free methods such as UL and RL have low complexity during training data generation, their performance suffers in comparison to the label-equipped SL. Note that the UL still requires an optimization stage for each data instance. The RL is promising because of its standalone operation and the consequent ability to adapt to environmental changes albeit at the cost of long training times.
- The transmission overheads are significantly reduced in FL, which may be combined with other learning methods. For example, the combination of FL- and RL-based learning policies not only exhibits a communications-efficient model training but also provides environmental adaptation.
- DL-related challenges include massive data collection, model training, and environment adaptation. These should be addressed simultaneously to provide a reliable DL architecture for the next-generation IRS-assisted wireless systems. Specifically, the combination of FL and RL should be fed with the collection of huge datasets and massive neural networks to yield a robust DL architecture.
- In IRS-assisted CF massive MIMO, multi-hop channel acquisition and low-complexity beamforming techniques are of great interest in the future. There has been recent progress in realizing IRS-assisted systems for THz communications. Another application of current interest is ISAC, where smart radio environments enabled by IRS provide additional degrees-of-freedom.

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