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GAN-based Channel Estimation for IRS-aided Communication Systems

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***Abstract*—This paper proposes a generative adversarial network (GAN) based channel estimation scheme for intelligent reflecting surface (IRS)-aided single-input multiple-output (SIMO) communication systems. The proposed novel GAN-based deep learning technique is efficient to estimate channels in IRS-aided wireless communication systems with high accuracy. The generator of GAN can reproduce data whose distributions are similar to the actual underlying channel. Consequently, the proposed approach does not require the statistical distribution of the underlying channel to be known in advance. Simulation results prove that the proposed GAN-based channel estimation approach outperforms the conventional least square estimation (LSE) approach significantly in terms of estimation accuracy as well as provides better performance than a fully connected deep neural network (DNN) and convolutional neural network (CNN)-based methods.**

***Index Terms*—Intelligent Reflecting Surface, Generative Adversarial Network, Artificial Intelligence, Channel Estimation, 6G.**

I. Introduction

In order to support the rising demand for ubiquitous wireless connectivity anywhere in the upcoming Internet-of-Everything (IoE) era, along with the soaring data-hungry applications development, fifth-generation (5G) cellular networks may not be adequately efficient to meet the demands in terms of capacity. This observation leads the researchers to carry out cutting-edge research to explore newer dimensions in upcoming sixth-generation (6G) cellular technology. Intelligent reflecting surface (IRS) is a key enabler of data transmission technology, with a vision to be deployed in 6G cellular communication systems to significantly enhance spectral efficiency. IRS is the advanced version of massive multiple-input multi-output (mMIMO) data transmission system [1], which is the prime transmission technology in 5G cellular networks. IRS is a controllable metasurface comprised of a large number of passive reflecting elements (PREs) that use very little power to control the phase and/or amplitude changes of incident signals to the IRS [2] - [5].

For efficient data detection at the receiver and precoding at the transmitter, the system requires channel state information (CSI) to be known. When the IRS consists of fully passive elements, the direct channel estimation of the link between the passive IRS and an active transceiver node becomes complicated and cumbersome owing to having a large number of channel reflecting coefficients and no active radio frequency (RF) chain. To encounter these challenges, setting the limitation of pilot sequence length equal to or greater than the number of receiver antennas leverages the training overhead in the channel estimation process. The primary challenges in fully passive IRS channel estimation of the uplink communication systems are the joint optimization of orthogonal pilot sequences, the reflection pattern of the reflective elements, and the efficient method to accurately estimate cascaded channels [2]. The statistical signal processing method least square estimation (LSE) is not optimal, hence, the technique may not estimate channels with good accuracy due to rapid change in the wireless propagation environment, data traffic pattern, multi-user interference, and underlying non-Gaussian noise. In this circumstance, the fusion of artificial intelligence (AI) techniques can smartly and efficiently shed light on wireless channel estimation with high accuracy and low runtime complexity compared to the conventional statistical signal processing approach by approximating complicated computations.

Deep learning-based data-driven approaches have widely been explored in channel estimation and prediction of IRS-aided communication systems [6] - [8]. It is shown that deep learning approaches are capable of estimating multi-dimensional channel data with relatively better accuracy than statistical signal processing methods [9] - [11]. On the other hand, generative adversarial networks (GANs) are comprised of a pair of convolutional neural networks known as generator and discriminator, are gaining significant popularity and being regarded as a promising technique in a wide range of sectors including channel estimation of communication systems in recent times [12] - [14].

To the best of our knowledge, GAN-based channel estimation for IRS-assisted communication systems has not yet been addressed in the literature. In this paper, we propose GAN-based channel estimation for an IRS-assisted single-input multiple-output (SIMO) narrowband communication system. The primary benefit of the proposed novel approach is that the GAN-based approach can determine the distribution of channel samples without using pilot signal information in the initial training phase. Once trained, the backpropagation optimization technique can accurately estimate the channel exploiting the GANs efficiency to analyze multi-dimensional correlated channel data. We have demonstrated that the GAN-based generative model-driven approach can estimate IRS cascaded channels with significantly better accuracy compared to the LSE method and even better than the deep neural network approach.

The rest of the paper is organized as follows. Section II

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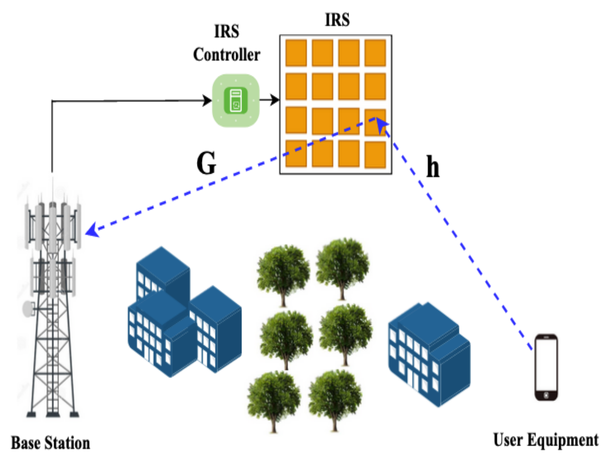

Fig. 1: IRS-aided single user SIMO system.

describes the system model. In section III, the proposed GAN model and the baseline schemes have been illustrated. The discussion on simulation results has been included in section IV. Finally, section V concludes the paper.

II. System Model

In Fig. 1, we consider a time division duplex (TDD) integrated IRS-aided narrowband flat fading uplink wireless transmission system with a base station (BS), an IRS panel, and a user. We assume the BS consists of M antennas, the user is comprised of a single antenna, and the IRS panel is equipped with L PREs. Each reflecting element $l \in \{1, 2, ..., L\}$ can reflect the incident signal. The complex reflection coefficient of lth PRE can be denoted as $\phi_l = \beta_l e^{j\alpha_l}$, where, the amplitude gain and the phase shift of lth element are represented by $\beta_l \in [0, 1]$ and $\alpha_l \in [0, 2\pi)$ respectively. Thus, the reflection coefficient matrix becomes $\mathbf{\Phi} = \text{diag}\ (\phi_1, \phi_2, ..., \phi_L)$, where, diag$(., ., .)$ represents the diagonal matrix. Refer to Fig. 1, due to blockage, we assume there is no direct line-of-sight (LoS) communication between user equipment (UE) to BS, and IRS aids BS and UE in data transmission. It is worth noting that the end-to-end propagation channel between BS and UE consists of the BS-to-IRS and IRS-to-UE communication links via IRS. As all the reflecting elements at IRS are assumed to be passive, the estimation of individual channel gains for BS-to-IRS and IRS-to-UE links cannot be conducted in a straightforward manner [2]. Therefore, estimation of the end-to-end cascaded channels (for a given $\mathbf{\Phi}$) between BS and UE via IRS is a feasible approach. However, because of the large L, the computational complexity of estimating the cascaded channels increases significantly. Our aim in this paper is to leverage GAN to develop a channel estimation scheme that strikes a balance between performance and (run-time) complexity [3]. In this paper, we develop a GAN-aided channel estimation scheme for two modes of operation; a) sequential on-off and b) all-on of the PREs [2].

A. Sequential On-Off

In the sequential on-off approach, the UE-IRS-BS cascaded channels are estimated sequentially by activating one of the PREs (while turning off $L-1$ elements) of IRS at a time. We assume the UE transmits the orthogonal pilot signals $\boldsymbol{x}_p \in \mathcal{C}^{1\times\tau}$ of length $\tau \geq 1$ (in samples) for channel estimation. The channels of UE-to-IRS and IRS-to-BS communication links are assumed to follow independent and identically distributed (i.i.d.) Rician fading because of the high likelihood of the presence of LoS communication link. Considering the normalized power constraint with a signal-to-noise ratio (SNR) denoted by γ, the received signal at the BS when $l \in \{1, 2, \cdots, L\}$ is active can be written as

$$\boldsymbol{Y}_l = \sqrt{\gamma}\boldsymbol{G}_l^H \phi_l h_l \boldsymbol{x}_p + \boldsymbol{N}_l \tag{1}$$

where, $\boldsymbol{Y}_l \in \mathcal{C}^{M\times\tau}$ is the received signal matrix at BS when $l \in \{1, 2, \cdots, L\}$ PRE is active, $\boldsymbol{G}_l \in \mathcal{C}^{1\times M}$ is the matrix of channel gains between PRE $l \in \{1, 2, \cdots, L\}$ and BS, h_l is the channel gain between UE to PRE $l \in \{1, 2, \cdots, L\}$, and $\boldsymbol{N}_l \in \mathcal{C}^{M\times\tau}$ is the additive white Gaussian noise (AWGN) matrix. It is worth mentioning that each element of $\boldsymbol{G}_l^H$ and h_l are i.i.d Rician fading with Rice factors $K_{\boldsymbol{G}_l}$ and K_{h_l}, respectively. Each element of $\boldsymbol{n}_l$ follows Gaussian distribution with zero-mean and unit variance. Our objective is to estimate the cascaded channel $\mathcal{H}_l = \boldsymbol{G}_l^H h_l$ from the received signal $\boldsymbol{y}_l$ and known $\boldsymbol{x}_p$ when PRE $l \in \{1, 2, \cdots, L\}$ is turned on by the proposed GAN-based channel estimation scheme. It is worth pointing out that we perform the estimation of cascaded channels sequentially to obtain the estimates of $\mathcal{H}_1, \mathcal{H}_2, \cdots, \mathcal{H}_L$ of all the cascaded channels between UE and BS. Although this sequential on-off approach is a simple channel characterization method to tackle IRS channels, it yields high latency in signal processing and results in weak received signal strength due to having only one reflecting element turned on at a time [2], [4].

B. All-On

In this mode of operation, the UE-IRS-BS cascaded channels are estimated when all the PREs of IRS are turned on [15]. Let us denote $\boldsymbol{G} \in \mathcal{C}^{L\times M}$ as the channel matrix from IRS to BS and $\boldsymbol{h} \in \mathcal{C}^{L\times 1}$ as the channel gain vector from UE to IRS. Considering $\boldsymbol{x}_p \in \mathcal{C}^{1\times\tau}$, where $\tau \geq L$, let us introduce $\boldsymbol{U} = [\boldsymbol{u}_1 \boldsymbol{u}_2 ... \boldsymbol{u}_L]$ that satisfy $\boldsymbol{U} = \boldsymbol{G}^H \text{diag}(\boldsymbol{h})$, where $\boldsymbol{u} \in \mathcal{C}^{M\times 1}$. The phase shift matrix $\mathbf{\Gamma} \in \mathcal{C}^{\tau\times L}$ containing phase-shifts of L PREs for τ samples in a given coherence time interval can be defined as follows:

$$\mathbf{\Gamma} = \begin{bmatrix} \phi_{1,1} & \cdots & \phi_{1,L} \\ \phi_{2,1} & \cdots & \phi_{2,L} \\ . & \cdots & . \\ . & \cdots & . \\ \phi_{\tau,1} & \cdots & \phi_{\tau,L} \end{bmatrix},$$

where $\phi_{t,l}$ represents the phase reflection coefficient for sample $t \in \{1, 2, \cdots, \tau\}$ and $l \in \{1, 2, \cdots, L\}$. Moreover, we denote $\boldsymbol{Q} = \mathbf{\Gamma} \otimes \boldsymbol{I}_M$, where $\boldsymbol{Q} \in \mathcal{C}^{\tau M\times ML}$ and $\boldsymbol{I}_M \in \mathcal{C}^{M\times M}$ is the identity matrix. The operator $\otimes$ represents the Kronecker product. Defining the pilot sequence matrix $\boldsymbol{X} \in \mathcal{C}^{M\tau\times M\tau}$ for a given coherence time interval as $\boldsymbol{X} = \text{diag}\ (x_1\mathbf{1}_M, x_2\mathbf{1}_M, ..., x_\tau\mathbf{1}_M)$, where $\mathbf{1}_M \in \mathcal{C}^{M\times 1}$ is a vector of ones and x_i, $i \in \{1, 2, \cdots, \tau\}$ are the elements of $\boldsymbol{x}_p$. Let us introduce $\boldsymbol{R} = \boldsymbol{X}\boldsymbol{Q}$, where $\boldsymbol{R} \in \mathcal{C}^{\tau M\times ML}$ and $\mathbf{\Theta} = [\boldsymbol{u}_1^T, \boldsymbol{u}_2^T, \cdots, \boldsymbol{u}_L^T]^T$. Here, $\mathbf{\Theta} \in \mathcal{C}^{ML\times 1}$ denotes the vector of channel gains when all PREs are on. The received signal $\boldsymbol{z}$ at BS while setting all PREs active (turned on) over τ samples can be represented as

$$\boldsymbol{z} = \sqrt{\gamma}\boldsymbol{R}\mathbf{\Theta} + \boldsymbol{w} \tag{2}$$

where $\boldsymbol{z} \in \mathcal{C}^{\tau M\times 1}$. Here, $\boldsymbol{w} \in \mathcal{C}^{\tau M\times 1}$ is the AWGN noise vector, where each element follows Gaussian distribution with zero-mean and unit variance. In this mode of operation, our goal is to precisely estimate $\mathbf{\Theta}$, which essentially contains all the elements of the cascaded channels.

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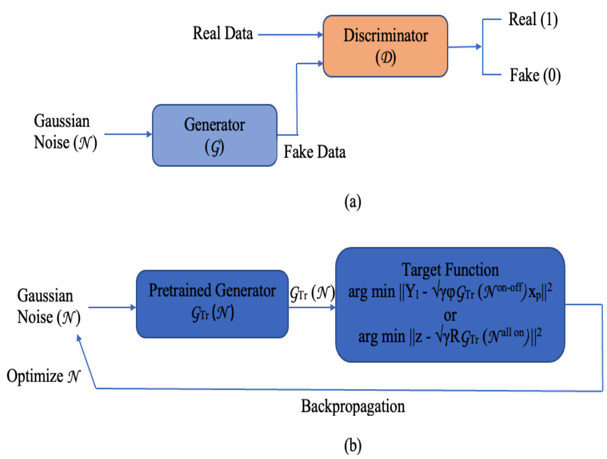

Fig. 2: (a) Training GAN (b) Real-time IRS channel estimation with GAN.

III. Proposed GAN-based IRS Channel Estimation

In this section, we explain how to configure different parts of GAN model for the proposed data-driven channel estimation scheme of the considered IRS-aided communication system. Further, we describe the baseline schemes to compare the performance of our proposed scheme.

A. GAN-based IRS Cascaded Channel Estimation

The zero-sum, min-max game theory over two adversarial networks is the foundation of GANs [16]. By competing two convolutional neural networks (the generator and the discriminator) against one another, GANs create fresh synthetic data that resembles real data distribution. The generator makes an effort to accurately represent the real data distribution while generating new data samples. On the other hand, the discriminator is typically a binary classifier that makes an effort to intelligently distinguish between real and generated fake data as precisely as feasible. Since GAN has the ability to reproduce data samples having the same distribution as the actual data samples by optimizing the generator, thus, it can generate increased length data sequence which favors channel estimation with high accuracy supported by Cramer-Rao lower bound law [14].

Proposed GAN Architecture: Refer to Fig. 2(a), generator $\mathcal{G}$ attempts to create a fake sample data by using the Gaussian random noise vector $\mathcal{N}$ as input. The generated fake data is then sent to the discriminator. The discriminator $\mathcal{D}$ is a binary classifier that simultaneously examines real and fake samples produced by the generator in an effort to distinguish between the real data of the channel gain and the generated fake data of the channel gain. Based on the results of the discriminator, the parameters of the generator are optimized while training to regenerate fake samples similar to the real data distribution. In this work, we adopt the backpropagation concept of the pretrained generator model [13] in order to identify the optimized noise vector $\mathcal{N}_{opt}$. Instead of using Wasserstein GAN (WGAN) [13], we implemented an optimized Deep Convolutional GAN (DCGAN) model in our considered system model. DCGAN performs better for a relatively large dimensional problem (e.g., channel estimation problem in IRS-assisted communication systems). DCGAN has more stable training functionality, hence, it results in quick convergence [17] - [19]. Although the WGAN model has a more insightful cost function than the DCGAN model, WGAN does not perform well while configured with a momentum-based optimizer like Adam [20]. The training of GANs is executed offline using Gaussian random noise $\mathcal{N}$. Note that the training datasets are generated over the entire range of γ. Once trained, the generator model is saved and then the pretrained generator model is optimized to determine $\mathcal{N}_{opt}$ computing the corresponding minimum value of the target function. The optimization operation is accomplished as

$$\mathcal{N}_{opt}^{\text{on-off}} = \arg\min ||\boldsymbol{Y}_l - \sqrt{\gamma}\phi_l \mathcal{G}_{\text{Tr}}(\mathcal{N}^{\text{on-off}})\boldsymbol{x}_p||^2 \tag{3}$$

and

$$\mathcal{N}_{opt}^{\text{all-on}} = \arg\min ||\boldsymbol{z} - \sqrt{\gamma}\boldsymbol{R}\,\mathcal{G}_{\text{Tr}}(\mathcal{N}^{\text{all on}})||^2 \tag{4}$$

for sequential on-off and all-on operations, respectively. Therefore, the corresponding generator model of the optimized noise vector determines the estimation of the cascaded channels as $\hat{\mathcal{H}}_l = \mathcal{G}_{\text{Tr}}(\mathcal{N}_{opt}^{\text{on-off}})$ and $\hat{\boldsymbol{\Theta}} = \mathcal{G}_{\text{Tr}}(\mathcal{N}_{opt}^{\text{all-on}})$ for sequential on-off and all-on schemes, respectively. Here, $\hat{\mathcal{H}}_l$ and $\hat{\boldsymbol{\Theta}}$ represent the estimated channel gains for sequential on-off and all-on schemes, respectively.

Algorithm 1 Real-Time GAN-based IRS Channel Estimation

Input: Gaussian random noise $\mathcal{N}$, actual channel samples $\mathcal{H}_l$ ($\boldsymbol{\Theta}$) for sequential on-off (all-on) scheme
Output: Estimated channel gain $\hat{\mathcal{H}}_l$ ($\hat{\boldsymbol{\Theta}}$) for sequential on-off (all-on) scheme

1: **Train** the GAN model $\mathcal{G}$ offline, generate $\hat{\mathcal{H}}_l$ ($\hat{\boldsymbol{\Theta}}$) for sequential on-off (all-on);
2: **Save** the trained generator model $\mathcal{G}_{\text{Tr}}$;
3: **Load** $\mathcal{G}_{\text{Tr}}$, $\boldsymbol{y}_l$ ($\boldsymbol{z}$), and $\boldsymbol{x}_p$;
4: **for** each iteration j **do**
5: $\quad\mathcal{G}_{\text{Tr}}(\mathcal{N})$;
6: $\quad$Calculate $||\boldsymbol{y}_l - \mathcal{G}_{\text{Tr}}(\mathcal{N}^{\text{on-off}})\boldsymbol{x}_p||^2$ ($||\boldsymbol{z} - \boldsymbol{R}\,\mathcal{G}_{\text{Tr}}(\mathcal{N}^{\text{all-on}})||^2$) for sequential on-off (all-on);
7: **end for**
8: $\quad$Obtain $\mathcal{N}_{opt}^{\text{on-off}}$ ($\mathcal{N}_{opt}^{\text{all-on}}$)
9: $\quad$Calculate $\hat{\mathcal{H}}_l$ ($\hat{\boldsymbol{\Theta}}$)
10: **return** Output

Training Arrangements: In this work, we use deep convolutional GAN architecture [17] for channel estimation of IRS-aided communication systems. It is worth noting that we generated the input for our considered generator model following a standard Gaussian distribution with zero mean and unit variance, rather than the uniform distribution used in [17]. Furthermore, adopting a Gaussian distribution for the input signal of the generator model is crucial in our considered IRS-assisted system, as the underlying noise is Gaussian, and our aim is to minimize the search space for our proposed non-linear L_2-norm-based channel estimation scheme. GAN architecture employs deep convolution neural networks (CNN) for both generator and discriminator networks to provide stable training. We have employed various activation functions (AF) for the generator and discriminator models to accurately capture the data suitable for different layers within the network models. In the considered GAN model in Fig. 3, the first layer of the generator consists of a fully connected layer followed by a rectified linear unit (ReLU) AF and batch normalization layer. Then the input data is reshaped into a three-dimensional (3D) vector. The following two layers are the Conv2DTranspose (two-dimensional transposed

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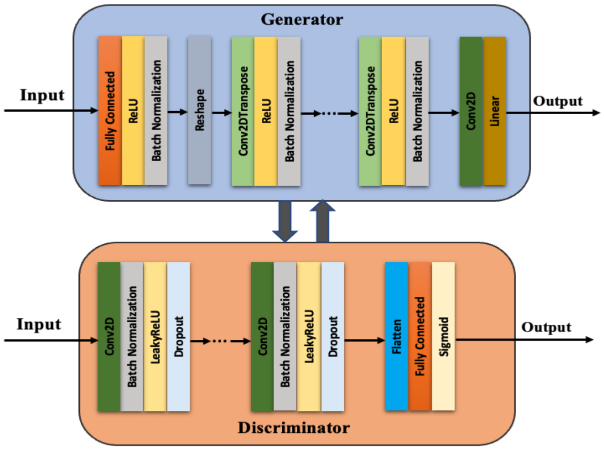

Fig. 3: GAN schematic diagram.

convolution) layer formed with kernel size $(a \times a)$, strides $(c \times c)$, activation ReLU and batch normalization layer. The Conv2DTranspose layer performs upsampling and convolution simultaneously. The upsampling increases the dimension of the data of the previous layer. The final layer is the output layer, consisting of a Conv2D (two-dimensional convolution) layer with a 'linear' AF and a kernel size of $(a \times a)$. The generator model upsamples the input data to generate the desired output dimension. On the other hand, the first two layers of the discriminator network are composed of a Conv2D layer with a kernel size of $(b \times b)$ and strides $(c \times c)$, followed by a batch normalization layer, a leaky rectified linear unit (LeakyReLU) AF, and a dropout layer. The negative slope coefficient of LeakyReLU is set to $\alpha = 0.2$, and the dropout layer rate is set to 0.4, which represents the fraction of input units to be dropped during the training process. Since the last layer is a fully connected layer with a single neuron, we added a 'Flatten' layer to make the dimension of the last layer compatible with the previous layer's multi-dimensional data. The AF 'sigmoid', the loss function 'cross entropy', and the optimizer 'Adam' are included in the last layer. The discriminator network downsamples the input data by halves.

The parameters in the offline training phase can be denoted as $\mathcal{E}_s$ a sequence of random Gaussian noise and $\mathcal{F}_s$ be the corresponding output sequence of channel gain from $\mathcal{G}$ model, where s represents the total number of sequences. Thus, the input-output pair of training datasets can be mathematically written as $\{(\mathcal{E}_1, \mathcal{F}_1), (\mathcal{E}_2, \mathcal{F}_2), ..., (\mathcal{E}_s, \mathcal{F}_s)\}$. $\mathcal{E}_s$ is chosen as latent dimension $\times$ number of samples, where, the latent dimension $\mathcal{L}$ is a random number, and the number of samples equal to the size of the dataset. The parameters in the optimization stage (as defined in eqs. (3) and (4)) during the online channel estimation phase can be expressed by $\mathcal{Y}_s$ and $\mathcal{X}_s$, denoting a sequence of the received signal and input pilot sequence, respectively. Thus, the relation can be mathematically represented as $\{(\mathcal{Y}_1, \mathcal{F}_1, \mathcal{X}_1, \mathcal{E}_1), (\mathcal{Y}_2, \mathcal{F}_2, \mathcal{X}_2, \mathcal{E}_2), ..., (\mathcal{Y}_s, \mathcal{F}_s, \mathcal{X}_s, \mathcal{E}_s)\}$, where the minimum value of the target function is computed using the sequences $\mathcal{Y}_s, \mathcal{F}_s, \mathcal{X}_s$ and the corresponding $\mathcal{E}_s$ is the optimized noise sequence. $\mathcal{Y}_s, \mathcal{F}_s$, and $\mathcal{X}_s$ represented as $M \times L \times 2$ real-valued matrices in the computation process. Hence, increasing L increases the training overhead significantly for both modes of the IRS. Since the DCGAN training process is faster than the WGAN, thus, the DCGAN model is more efficient for channel estimation than the WGAN model in the considered system model. The stochastic gradient descent (SGD) algorithm is used in the training phase to optimize the weights of the GAN model. Both the generator and discriminator model optimize their performance simultaneously while executing the training phase. The training dataset has been divided into batches per epoch. The discriminator model gets updated on weight parameters in two separate batches; one batch is used for updates on real data and another batch is used for updates on generated fake data.

B. Computational Complexity

The computational complexity in forward and backward propagation in the offline training phase of the GAN scheme (considering both generator and discriminator networks) is represented as $\mathcal{O}\left(2\left(H_{Fc,I}I_{\mathcal{G}} + C^2K^2\sum_{t=1}^{T_{\mathcal{G}}} D_t^2\right)VU\right)$ + $\mathcal{O}\left(2\left(C^2K^2\sum_{t=1}^{T_{\mathcal{D}}} D_t^2 + H_{Fc,O}E\right)VU\right)$, where C, K, D_t, t, $H_{Fc,I}$, $I_{\mathcal{G}}$, $H_{Fc,O}$, E, U, and V represent the channel size, kernel size, feature map of the respective hidden layer, number of hidden layers, number of neurons in fully connected layer at generator model, input of generator, number of neurons in fully connected layer at discriminator model, number of features in fully connected layer at discriminator model, number of epochs, and number of batches per epoch respectively. Note that the computational complexity in optimizing the GAN model varies with the IRS mode of operation. In sequential on-off mode, the computational complexity in optimizing the GAN model is linearly incremental with the increase of L, since only one PRE is turned on at a time. On the contrary, for the all-on mode of operation, the optimization steps of the GAN model are executed once for L number of PREs, since all PREs are on. While comparing our proposed scheme with [9], it can be inferred that both models show polynomial complexity.

C. Advantages of GAN in Cascaded Channel Estimation

The proposed data-driven channel estimation scheme exhibits low run-time (online) computational complexity to estimate channel gains for IRS-aided wireless communication systems compared to state-of-the-art estimation schemes, e.g., minimum mean square error (MMSE) or conventional maximum likelihood estimation (MLE) schemes. Because of the cascaded nature (non-Gaussian distribution) of the underlying channel (high dimensional matrix) between BS and UE, it is mathematically intractable to develop a linear MMSE (LMMSE) scheme to estimate the channel [10]. The MLE requires either matrix inversion or infinitely large search space and hence requires more computations to estimate the channel in real-time. However, leveraging the GAN architecture assists in capturing the correlation of the high dimensional cascaded channel matrix by exploiting its inherent mechanism and thereby reduces the search space for L_2-norm estimation scheme.

D. Baseline Approaches

Deep Neural Network (DNN): We consider a DNN model to compare its performance with the proposed GAN model. The DNN model takes the output signal of the system model as input and solves the computational model to provide the output estimated channel gain as the actual channel. The DNN model is formed with five fully connected layers, including input and output layers, out of which three layers are hidden layers.

Convolutional Neural Network (CNN): A convolutional neural network (CNN) model has been considered for performance comparison with the proposed GAN model. The first layer of the CNN model is the input layer, which captures the received signal of the considered system. The three middle layers are the core layers, where the majority of computations and learning occur. Each stack of middle layers consists of a Conv2D (two-dimensional convolution) layer, batch normalization layer, activation ReLU, and AveragePooling2D (two-dimensional average pooling) layer. The final layer is the fully connected output layer.

Least Square Estimation (LSE): We consider the LSE method as another baseline approach. The estimated channel using the LSE method can be expressed as

$$\hat{\mathcal{H}}_l = ((\boldsymbol{\zeta}\boldsymbol{\zeta}^H)^{-1}\boldsymbol{\zeta}\boldsymbol{y}_l^H)^H \tag{5}$$

and

$$\hat{\boldsymbol{\Theta}} = ((\boldsymbol{R}^H\boldsymbol{R})^{-1}\boldsymbol{R}^H)\boldsymbol{z} \tag{6}$$

for sequential on-off and all-on modes of operations, respectively, where $\boldsymbol{\zeta} = \sqrt{\gamma}\phi_l\boldsymbol{x}_p$.

IV. Simulation Results

In this section, we present the numerical results for the proposed data-driven channel estimation scheme to evaluate their performances and compare them with the considered baseline schemes. We first show the impact of training the GAN model on the estimation error over a range of SNR while considering different training parameters. We then illustrate the comparative performance evaluations of the proposed scheme with baseline approaches in terms of normalized mean square error (NMSE) that can be calculated as follows:

$$\text{NMSE} = \mathbb{E}\Big\{\frac{||\boldsymbol{\varrho} - \hat{\boldsymbol{\varrho}}||^2}{||\boldsymbol{\varrho}||^2}\Big\}, \tag{7}$$

where $\boldsymbol{\varrho} \in \{\mathcal{H}_l, \boldsymbol{\Theta}\}$ and $\hat{\boldsymbol{\varrho}} \in \{\hat{\mathcal{H}}_l, \hat{\boldsymbol{\Theta}}\}$. The dataset generation for training and testing is accomplished using MATLAB via Monte Carlo simulations, and the training and optimization operations are performed using the Python TensorFlow framework. In particular, we generate 50,000 realizations of random data samples for training and 50,000 realizations for testing purposes for both the proposed and baseline schemes. For all the considered experiments, we set $M = 8, L = 2^p$, $p = 3$, and $K_{G_l} = K_{h_l} = 10$ dB. While configuring the GAN model, we set $\mathcal{L} = 500$, $a = 4$, $c = 2$, and $b = 3$. Further, we consider 2000 epochs during the training phase while setting 1000 batches in each epoch. We consider real and imaginary parts separately while representing each signal in a 3D vector. The training parameters are tuned and remained the same throughout the entire simulations after a rigorous trial and error process while assuring the tradeoff between performances and computational complexity. The training is executed with the ADAM optimizer and a learning rate of 0.0002 for the proposed and baseline models to ensure a fair comparison. It is worth mentioning that the convolution blocks in the considered GAN model can efficiently analyze high dimensional correlated channel gain data samples due to the distinct architecture of the generative adversarial networks. The adversarial training process of the GAN model is pivotal to significantly reduce the suitable search range of channel gain in order to identify its correlation with the actual channel gain data samples.

Effect of GAN-parameters on Training: In Fig. 4, we demonstrate the impact of the number of epochs and the size of the training dataset on the accuracy of the proposed GAN-aided channel estimation scheme. We consider several configurations of training parameters by tuning the number of epochs and the size of training datasets. For each configuration, the estimation accuracy is calculated via NMSE as a function of SNR γ. We observe that increasing γ for each configuration increases the estimation performance and hence decreases the NMSE. Moreover, increasing the number of epochs and the size of datasets decreases the channel estimation error notably. However, increasing the size of the datasets beyond 50,000 and the number of epochs more than 4000 does not yield significant performance gain in terms of NMSE. It is worth mentioning that increasing the number of datasets and the number of training epochs essentially increases the training computations and time, hence, it requires a tradeoff between optimal performance and computational complexity.

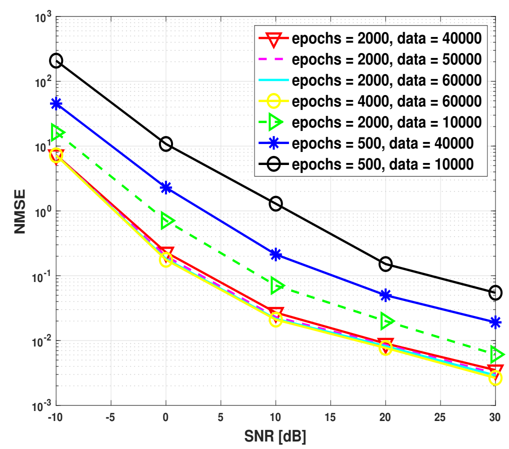

Fig. 4: Training impact of GAN on estimation error.

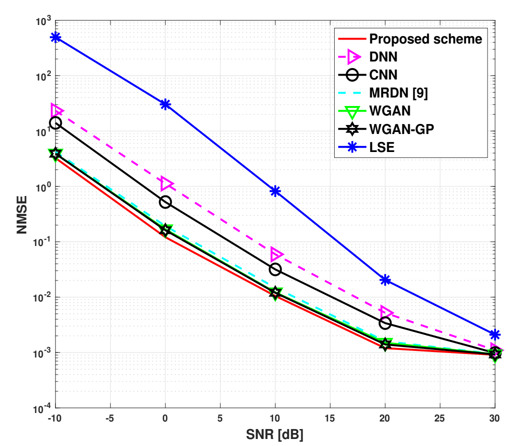

Fig. 5: Estimation error for IRS sequential on-off.

Comparison of Proposed Channel Estimation Scheme with Baseline Schemes: In Figs. 5 and 6, we demonstrate the effectiveness of the proposed GAN-based channel estimation scheme for sequential on-off and all-on schemes, respectively. In particular, we present the NMSE of the proposed and

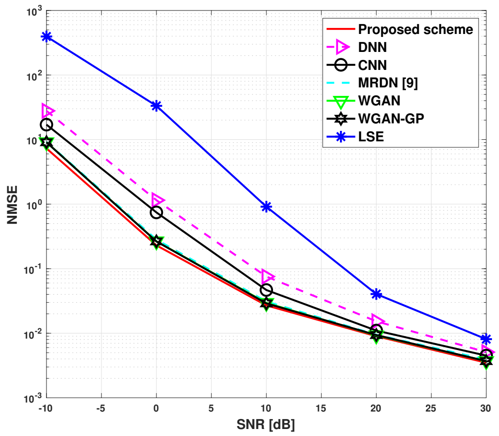

Fig. 6: Estimation error for IRS all-on.

baseline schemes as a function of γ. For both the considered sequential on-off and all-on schemes, we observe that NMSE decreases with increasing γ, as expected. It is seen that the NMSE performance of both sequential on-off and all-on modes of operation are almost similar, but the hardware complexity and device latency of the sequential on-off mode are much higher compared to all-on. The sequential on-off mode requires an additional switching mechanism to turn on-off the PREs of IRS in order to control the amplitude of the individual PRE that increases hardware complexity. Moreover, the proposed GAN-aided channel estimation scheme outperforms the LSE, DNN, and CNN schemes over the entire range of considered γ. However, the performance gap between the proposed and LSE schemes is large for low SNR and small for high SNR. For instance, denoting the performance improvement factor $\rho = \text{NMSE of Proposed Scheme}/\text{NMSE of LSE}$, $\gamma = 10$dB and $\gamma = 25$dB results in $\rho = 20$ and 4, respectively for all-on scheme. The NMSE performance is also compared with the multiple-residual dense network (MRDN) model proposed in [9], the WGAN [13], and the WGAN-GP [21]. The results demonstrate that the proposed GAN model can estimate the cascaded channels of IRS for both modes of operation with slightly lower error than [9], [13], and [21]. It is worth mentioning that adversarial networks can deeply analyze multi-dimensional data to extract the correlation features more efficiently during the training process while considering addressing different levels of noise power spectral density. On the contrary, the LSE scheme degrades the estimation accuracy in low SNR. However, the LSE approach includes matrix inversion and multiplication to compute cascaded channel gains that show less complexity than the proposed scheme. The deep convolutional layers of the generator and discriminator networks in the considered GAN yield enhanced performance in predicting highly correlated cascaded channels as long as the hyper-parameters are optimized efficiently.

V. Conclusion

In this paper, we proposed a novel GAN-based channel estimation method for IRS-aided communication systems. The benefits of using GAN to analyze the correlation of multi-dimensional channel data have been explored to leverage accurate channel estimation in IRS-assisted communication systems. Furthermore, it has been demonstrated that the optimized GAN-based approach can estimate actual IRS cascaded channels with greater accuracy compared to the LSE method. The proposed approach can also outweigh widely employed DNN and CNN solutions in terms of accuracy in estimating IRS cascaded channels. In future work, GAN-based channel estimation can be implemented in more complicated IRS-assisted communication systems and could be compared with some other highly optimized deep learning techniques to determine the best technique in order to ensure high accuracy in channel estimation.

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