

Learning to Beamform for Intelligent Reflecting Surface with Implicit Channel Estimate

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Abstract—Intelligent reflecting surface (IRS), consisting of massive number of tunable reflective elements, is capable of boosting spectral efficiency between a base station (BS) and a user by intelligently tuning the phase shifters at the IRS according to the channel state information (CSI). However, due to the large number of passive elements which cannot transmit and receive signals, acquisition of CSI for IRS is a practically challenging task. Instead of using the received pilots to estimate the channels explicitly, this paper shows that it is possible to learn the effective IRS reflection pattern and beamforming at the BS directly based on the received pilots. This is achieved by parameterizing the mapping from the received pilots to the optimal configuration of IRS and the beamforming matrix at the BS by properly tuning a deep neural network using unsupervised training. Simulation results indicate that the proposed neural network can efficiently learn to maximize the system sum rate from much fewer received pilots as compared to the traditional channel estimation based solutions.

I. INTRODUCTION

Intelligent Reflecting Surface (IRS), which is composed of a large number of reflective elements, can manipulate incident electromagnetic waves to the intended users by adjusting the phase response of each passive element [1], [2]. By intelligently adjusting its phase response which is a part of the signal propagation environment, the IRS can in effect cooperate with the transmitter in processing and transferring information to the receiver [1]. In addition, due to its passive and simple structure, the IRS requires very little energy to induce the desired phase shifts for signals reflection, and can be flexibly integrated into various objects (e.g., walls, ceilings), which enables a smooth deployment of IRS in existing wireless communication networks [1]. As a result, applications of IRS have been discussed in the literature for a wide range of communication scenarios, e.g., for improving network coverage [3], boosting wireless spectral efficiency [4], [5], reducing power consumption of data transmission [2] and enabling secure wireless communications [6].

However, most of the existing works assume that channel state information (CSI) is available at the base station (BS) when jointly optimizing the IRS reflection and BS beamforming patterns to achieve some network objective, e.g., to minimize the energy consumption [2] or to maximize the spectral efficiency [5]. In practice, CSI needs to be estimated. However, since the IRS consists of passive devices without the ability to perform active signal transmission and reception, it is challenging to obtain CSI at the IRS. Furthermore, it is observed that the number of elements of IRS has to be large in order to achieve higher beamforming gain [7], thus end-to-

end training often leads to excessive pilot training overhead. To address this issue, some works have proposed to solve the channel estimation problem based on binary reflection method [8] or by grouping IRS elements into sub-surfaces [9]. More recently, [10] proposes a compressed sensing based channel estimation method for multi-user IRS aided system, which reduces the training overhead significantly but requires the assumption of channel sparsity. Further, [11] proposes to reduce the training overhead by exploiting the common reflective channels among all the users. All these works fall into the paradigm of estimating the channels from the received pilot signals first, then solving the reflection optimization problems based on the estimated channels.

The main point of this paper is that by taking a machine learning approach, it is possible to bypass the explicit channel estimation altogether. Our idea is that instead of estimating each of the channel coefficients, we can directly optimize the system objective based on the received pilots. By mapping the received pilots to the optimized IRS pattern directly, this paper shows that the training overhead can be significantly reduced.

In particular, this paper considers a sum-rate maximization problem for an IRS aided multi-user MIMO system. Given the received pilot signals, our proposed approach learns to configure the IRS pattern and beamforming at the BS directly for maximizing the sum rate of all the users, without first estimating the channel. The proposed approach is motivated by the success of using deep learning to optimize wireless communication systems without first estimating the channel [12], [13]. In particular, [12] shows that based on the geographical locations of the users, deep learning approach is able to learn the optimal scheduling without channel estimation. Location information is also utilized in [13] to configure the IRS for indoor signal focusing using a deep learning approach.

However, the achievable rates are not merely functions of the locations, but also functions of small-scale fading that cannot be fully characterized by the transmitter and receiver locations. For this reason, this paper proposes to leverage the received pilots to design the IRS reflecting pattern and the beamforming matrix in recognition of the fact that the received pilots contain rich information of both the user locations as well as its surrounding communication environments. In particular, we formulate the sum-rate maximization problem as a variational optimization problem whose optimization variables are functionals—mapping from the received pilots to the phase shifts at IRS and beamforming matrix at the BS. Our approach can be viewed as an implicit channel estimation,

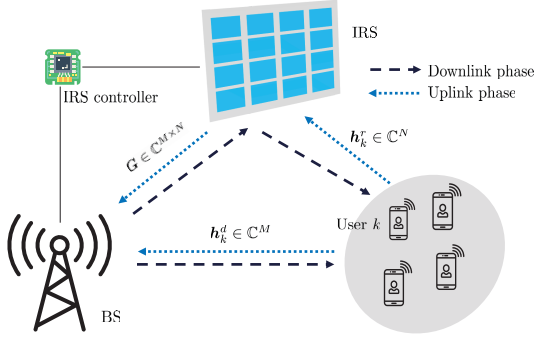


Fig. 1. IRS assisted multi-user MIMO system

which we show in this paper is a more efficient way of utilizing the pilots.

The resulting variational optimization problem is computationally difficult to solve. We thus propose to parameterize the corresponding mapping as a neural network, and learn the neural network parameters from the training data in an unsupervised manner. We numerically show that the proposed deep learning approach significantly outperforms the traditional channel estimation based approach in that much fewer pilots are required.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

Consider an IRS assisted multi-user MIMO system where K single-antenna users are served by a BS with M antennas. An IRS equipped with N passive elements is deployed between the BS and users essentially serving as a relay. With an IRS controller, the IRS works cooperatively with the BS to control the reflected phase of incident signals by adjusting its phase array. Specifically, denote $\mathbf{v} = [e^{j\theta_1}, e^{j\theta_2}, \dots, e^{j\theta_N}]$ as the chosen phase shifts at IRS, where $\theta_i \in [0, 2\pi)$ is the phase shift of the i -th element. As shown in Fig. 1, let $\mathbf{G} \in \mathbb{C}^{M \times N}$ be the channel matrix between the IRS and the BS, and $\mathbf{h}_k^r \in \mathbb{C}^N$, $\mathbf{h}_k^d \in \mathbb{C}^M$ be the channel vectors between the IRS and user k , and between the BS and the user k , respectively. We assume that the channel coefficients remain constant during a coherence block, but change independently from block to block. Let $s^k \in \mathbb{C}$ be the symbol to be transmitted from the BS to user k , and the transmitted symbols are modeled as independent random variables with zero mean and unit variance. The received signal r_k at the user k is thus given by

$$r_k = \sum_{k=1}^K (\mathbf{h}_k^d + \mathbf{G} \text{diag}(\mathbf{v}) \mathbf{h}_k^r)^\top \mathbf{w}_k s_k + n_k \quad (1)$$

$$= \sum_{k=1}^K (\mathbf{h}_k^d + \mathbf{A}_k \mathbf{v})^\top \mathbf{w}_k s_k + n_k, \quad (2)$$

where $\mathbf{A}_k = \mathbf{G} \text{diag}(\mathbf{h}_k^r) \in \mathbb{C}^{M \times N}$ is the cascaded channel between the user and the BS through reflection at the IRS, $\mathbf{w}_k \in \mathbb{C}^M$ is the beamforming vector at the BS intended for

user k with power constraint $\sum_{k=1}^K \|\mathbf{w}_k\|^2 \leq P$, and $n_k \sim \mathcal{CN}(0, \sigma_0^2)$ is the additive Gaussian noise.

Under the above settings, the achievable rate R_k of user k can be computed as

$$R_k = \log \left(1 + \frac{|(\mathbf{h}_k^d + \mathbf{A}_k \mathbf{v})^\top \mathbf{w}_k|^2}{\sum_{i=1, i \neq k}^K |(\mathbf{h}_i^d + \mathbf{A}_i \mathbf{v})^\top \mathbf{w}_i|^2 + \sigma_0^2} \right). \quad (3)$$

The beamforming vectors \mathbf{w}_k 's at the BS and phase shifts \mathbf{v} at the IRS can be jointly optimized to maximize the sum rate, i.e., $\sum_k R_k$ [5]. To optimize the transmit beamforming at the BS and the reflection coefficients at the IRS, the knowledge of the cascaded channel matrix \mathbf{A}_k and the channel vector \mathbf{h}_k^d for $k = 1, \dots, K$ is required. Therefore a pilot transmission phase before data transmission is needed for estimating \mathbf{A}_k 's and \mathbf{h}_k^d 's.

This paper assumes uplink-downlink channel reciprocity for channel estimation [8], i.e., the downlink channel is exactly the same as the uplink channel between any two antenna elements. In the pilot transmission phase, user k sends a pilot symbol $x_k(\ell)$ to the BS for $\ell = 1, \dots, L$. Thus the received signal $\mathbf{y}(\ell)$ at the BS can be expressed as

$$\mathbf{y}(\ell) = \sum_{k=1}^K (\mathbf{h}_k^d + \mathbf{G} \text{diag}(\mathbf{v}(\ell)) \mathbf{h}_k^r) x_k(\ell) + \mathbf{n}(\ell) \quad (4)$$

$$= \sum_{k=1}^K (\mathbf{h}_k^d + \mathbf{A}_k \mathbf{v}(\ell)) x_k(\ell) + \mathbf{n}(\ell), \ell = 1, \dots, L, \quad (5)$$

where $\mathbf{v}(\ell)$ is the phase shifts of IRS at time slot ℓ , $\mathbf{n}(\ell) \sim \mathcal{CN}(0, \sigma_1^2 \mathbf{I})$ is the additive Gaussian noise and L is the pilot length. Note that there are $(M+N)K + MN$ unknown channel coefficients in \mathbf{G} , \mathbf{h}_k^d 's and \mathbf{h}_k^r 's, $k = 1, \dots, K$. Since the number of elements in a typical IRS, N , is generally quite large (possibly in the hundreds), it is challenging to estimate the channels with limited-length pilots.

B. Problem Formulation

The main idea of this paper is that since the final goal is to optimize the rates R_k 's, instead of estimating all the channel coefficients, we can exploit the pilot phase more efficiently by mapping the received pilots directly to the optimized transmission strategy for rate maximization, in effect, bypassing channel estimation.

To this end, we propose to design the optimal beamforming vector \mathbf{w}_k 's and the reflection phase shifts \mathbf{v} based on the received pilots \mathbf{Y} directly, where $\mathbf{Y} = [\mathbf{y}(1), \mathbf{y}(2), \dots, \mathbf{y}(L)] \in \mathbb{C}^{M \times L}$ denote the received pilots in L symbol durations. Specifically, given the matrix \mathbf{Y} , our goal is to solve the following optimization problem

$$\begin{aligned} & \underset{\substack{\mathbf{W} = \mathbf{f}(\mathbf{Y}) \\ \mathbf{v} = \mathbf{g}(\mathbf{Y})}}{\text{maximize}} && \mathbb{E} \left[\sum_k R_k(\mathbf{v}, \mathbf{W}) \right] \\ & \text{subject to} && \sum_k \|\mathbf{w}_k\|^2 \leq P \\ & && |v_i| = 1, i = 1, 2, \dots, N, \end{aligned} \quad (6)$$

where $\mathbf{W} = [\mathbf{w}_1, \dots, \mathbf{w}_K]$ is the beamforming matrix at BS, f and g are functions that map the received pilots to the beamforming matrix \mathbf{W} and the phase shifts \mathbf{v} . The expectation here is over the fast-fading components of all the channels.

However, solving problem (6) is computationally challenging since it involves solving a variational optimization problem with non-convex constraints and non-convex objective function. To tackle this problem, we propose to learn the mapping functions f and g via deep learning. This is motivated by the universal approximation property of the neural networks [14]. But first, we discuss the conventional approach of uplink channel estimation followed by sum-rate maximization as a baseline solution to problem (6).

III. BASELINE METHOD

In this section, we present a baseline solution to solve the problem (6), which consists of an uplink channel estimation phase and a downlink sum-rate maximization phase. The downlink sum-rate maximization problem can be solved using the algorithm proposed in [5]. Below we focus on the channel estimation method.

A. Received Pilots

For channel estimation, we adopt the scheme proposed in [10] to design the pilots and uplink phase shifts for the purpose of decorrelating the received pilots at the BS for each user. In particular, the total training slots L is divided into τ sub-frames, each of which consists of $L_0 = K$ symbols (i.e., $L = \tau L_0$). In the t -th sub-frame, user k sends its pilot sequences $\mathbf{x}_k^H = [x_k(1), x_k(2), \dots, x_k(L_0)]$ to the BS, and the pilot sequences of all users are designed to be orthogonal to each other, i.e., $\mathbf{x}_{k_1}^H \mathbf{x}_{k_2} = 0$ if $k_1 \neq k_2$ and $\mathbf{x}_{k_i}^H \mathbf{x}_{k_i} = L_0$. Meanwhile, the IRS uses different phase shifts in different sub-frames, and keeps the phase shifts unchanged during each sub-frame to ensure that the overall measurement matrix is full rank.

Now we decorrelate the received pilots of all sub-frames for user k using the orthogonal pilots. In the sub-frame t , let $\mathbf{Y}(t) = [\mathbf{y}(1), \dots, \mathbf{y}(L_0)]$ denote the overall received pilots, we have

$$\mathbf{Y}(t) = \sum_{k=1}^K (\mathbf{h}_k^d + \mathbf{A}_k \mathbf{v}(t)) \mathbf{x}_k^H + \mathbf{N}(t), \quad t = 1, \dots, \tau, \quad (7)$$

where $\mathbf{N}(t) \sim \mathcal{CN}(\mathbf{0}, \sigma_1^2 L_0 \mathbf{I})$. By the orthogonality of the pilots, we can form $\mathbf{y}_k(t) \in \mathbb{C}^M$, i.e., the contribution from user k at the t -th sub-frame, as given by [10]

$$\mathbf{y}_k(t) = \mathbf{Y}(t) \mathbf{x}_k / L_0 = \mathbf{h}_k^d + \mathbf{A}_k \mathbf{v}(t) + \mathbf{n}(t) \quad (8)$$

$$\triangleq \mathbf{F}_k \mathbf{q}(t) + \mathbf{n}(t), \quad (9)$$

where $\mathbf{n}(t) = \mathbf{N}(t) \mathbf{x}_k / L_0$. Further, we define the combined channel matrix $\mathbf{F}_k \triangleq [\mathbf{h}_k^d, \mathbf{A}_k]$ and the combined phase shifts $\mathbf{q}(t) \triangleq [1, \mathbf{v}(t)^T]^T$.

Recall that we have τ sub-frames in total. By denoting $\mathbf{Y}_k = [\mathbf{y}_k(1), \dots, \mathbf{y}_k(\tau)]$ as the received pilots of the τ sub-frames, we have

$$\mathbf{Y}_k = \mathbf{F}_k \mathbf{Q} + \mathbf{N}', \quad (10)$$

where $\mathbf{Q} = [\mathbf{q}(1), \dots, \mathbf{q}(\tau)]$ and $\mathbf{N}' = [\mathbf{n}(1), \dots, \mathbf{n}(\tau)]$. The channel estimation problem is to estimate the combined matrix \mathbf{F}_k for $k = 1, \dots, K$. Typically, to ensure that the matrix \mathbf{Q} is full rank so that \mathbf{F}_k can be recovered successfully, we need at least $\tau = N + 1$, i.e., a total $(N + 1)K$ pilot symbols are needed. When $\tau = N + 1$, we can construct \mathbf{Q} to be a DFT matrix as suggested in [9]. For comparison purposes, we also consider the more general case where $\tau \neq N + 1$. In this case, \mathbf{Q} is not a square matrix, so we first construct a $d \times d$ DFT matrix \mathbf{Q}' with $d = \max(\tau, N + 1)$, then truncate \mathbf{Q}' by preserving the first τ columns and the first $N + 1$ rows.

We note here that more efficient channel estimation algorithms that take into account of the fact that different users' channels have a common component (i.e., the BS-to-IRS channel) can be constructed, but these algorithms typically require more restrictive conditions [10], [11].

B. Channel Estimation

To estimate the channel matrix \mathbf{F}_k from equation (10), we consider the minimum mean-squared error (MMSE) estimator, which is obtained by solving the following problem

$$\underset{h(\cdot)}{\text{minimize}} \quad \mathbb{E} [\|h(\mathbf{Y}_k) - \mathbf{F}_k\|_F^2]. \quad (11)$$

The optimal solution to problem (11) is given by [15]

$$\mathbf{F}_k^* = \mathbb{E}[\mathbf{F}_k | \mathbf{Y}_k]. \quad (12)$$

However, the optimal solution is computationally intensive to implement since it involves high dimensional integration. A low-complexity approach is to constrain the estimator h to be linear, which results in the linear MMSE (LMMSE) method. Then the solution to (11) has a closed-form solution as follows [15]

$$\hat{\mathbf{F}}_k = (\mathbf{Y}_k - \mathbb{E}[\mathbf{Y}_k]) \mathbb{E}[\mathbf{Y}_k^H \mathbf{Y}_k]^{-1} \mathbb{E}[\mathbf{Y}_k^H \mathbf{F}_k] + \mathbb{E}[\mathbf{F}_k]. \quad (13)$$

The estimates of \mathbf{h}_k^d , \mathbf{A}_k can be obtained from $\hat{\mathbf{F}}_k$ trivially. We should note that the linear restriction on the function h can result in a suboptimal solution to (11), it is only optimal when the unknown \mathbf{F}_k is Gaussian distributed.

IV. PROPOSED DEEP LEARNING METHOD

From the channel estimation problem (11), we see that problem (11) aims to recover every entry of \mathbf{F}_k using the squared error metric given the received pilots \mathbf{Y}_k . However, this is not the goal of the sum-rate maximization problem (6). Furthermore, mean squared error is not the optimal metric for the sum-rate maximization problem. Instead, this paper proposes to use a neural network based approach to solve problem (6), whose goal is to learn to maximize the sum rate from the received pilots directly. Namely, the mapping functions f and g of problem (6) are parameterized by a properly designed neural network.

To learn the mapping functions f and g , a fully connected neural network is trained, which takes the vectorized received pilots matrix $[\Re\{\mathbf{Y}\}, \Im\{\mathbf{Y}\}]$ as inputs, and outputs the real and imaginary parts of the intended beamforming matrix \mathbf{W} and phase shifts \mathbf{v} that maximize the sum rate. The proposed neural network architecture is shown in Fig. 2. In particular,

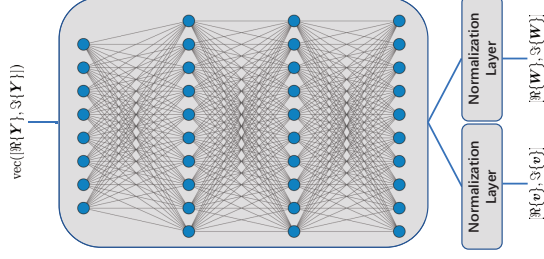


Fig. 2. Neural Network Architecture.

the mapping function f is parameterized by a fully connected neural network of size $2ML \times f_1 \cdots \times f_j \times 2MK$, which consists of j hidden layers of f_j neurons each. Similarly, the mapping function g is parameterized by a fully connected neural network of size $2ML \times f_1 \cdots \times f_j \times 2N$. As shown in Fig. 2, these two neural networks share the same layers before the last normalization layer to reduce the complexity of the neural network model. The normalization layer is to ensure that the final outputs \mathbf{W} and \mathbf{v} meet the constraints of problem (6). Specifically, an activation function $\sigma_W(\mathbf{W}) = \sqrt{P}\mathbf{W}/\|\mathbf{W}\|_F$ is used for the normalization layer with output \mathbf{W} ; an activation function $\sigma_v(v_i) = v_i/|v_i|, i = 1, \dots, N$ is used for the normalization layer with output \mathbf{v} .

Since the existing deep learning packages do not support complex-value operations, to compute the sum rate during the training phase, we rewrite the achievable rate R_k as a function of the real counterpart and imaginary counterpart of \mathbf{w}_k and \mathbf{v} as follows,

$$R_k = \log \left(1 + \frac{\|\gamma_k\|^2}{\sum_{i=1, i \neq k}^K \|\gamma_i\|^2 + \sigma_0^2} \right), \quad (14)$$

where

$$\gamma_i = \begin{bmatrix} \Re\{\mathbf{w}_i\} & -\Im\{\mathbf{w}_i\} \\ \Im\{\mathbf{w}_i\} & \Re\{\mathbf{w}_i\} \end{bmatrix} \cdot \left(\begin{bmatrix} \Re\{\mathbf{h}_k^d\} \\ \Im\{\mathbf{h}_k^d\} \end{bmatrix} + \begin{bmatrix} \Re\{\mathbf{A}_k\} & -\Im\{\mathbf{A}_k\} \\ \Im\{\mathbf{A}_k\} & \Re\{\mathbf{A}_k\} \end{bmatrix} \begin{bmatrix} \Re\{\mathbf{v}\} \\ \Im\{\mathbf{v}\} \end{bmatrix} \right). \quad (15)$$

Note that we need CSI to compute the sum rate, but only in the training phase, and not in the testing phase when predicting the optimal phase shifts and the beamforming matrix.

During training, the neural network learns to adjust its weights to maximize the sum rate, i.e., the objective function of problem (6) in an unsupervised manner, using the stochastic gradient descent method. The updates of the neural network parameters including computing the corresponding gradients can be automatically implemented in any deep learning framework such as Tensorflow [16].

Such an end-to-end training allows us to extract the information that we need to jointly design the beamforming matrix and phase shifts from the received pilots. As shown in the following section, the proposed deep learning method is able to solve problem (6) efficiently. Moreover, it is able to achieve a satisfactory performance with significantly reduced pilot length as compared to the baseline method.

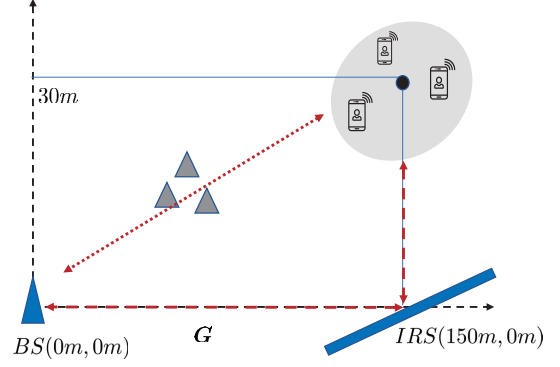


Fig. 3. Simulation layout of IRS assisted communication system.

V. SIMULATION RESULTS

In this section, we evaluate the performance of the proposed deep learning method in comparison to the channel estimation based baseline.

A. Setting

We consider an IRS assisted multi-user MIMO communication system as illustrated in Fig. 3, consisting of a BS with 4 antennas and an IRS with 100 passive elements. There are 3 users uniformly distributed in a circular area centered at (150m, 30m) with radius 10m. We assume that the direct link channel $\mathbf{h}_k^d \sim \mathcal{CN}(\mathbf{0}, \mathbf{I})$ follows Rayleigh fading, while the channel \mathbf{G} between BS and IRS, channel \mathbf{h}_k^r 's between IRS and users follow Rician fading, which are modeled as

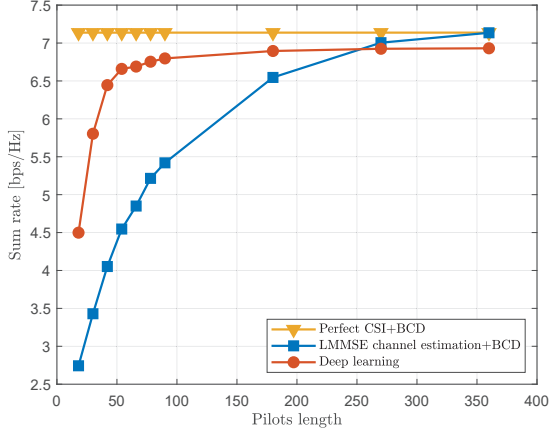
$$\mathbf{G} = \beta_1 \left(\sqrt{\frac{\varepsilon}{1+\varepsilon}} \mathbf{a}_M(\phi_1) \mathbf{a}_N(\phi_2)^H + \sqrt{\frac{1}{1+\varepsilon}} \mathbf{G}_0 \right), \quad (16)$$

$$\mathbf{h}_k^r = \beta_{2,k} \left(\sqrt{\frac{\varepsilon}{1+\varepsilon}} \mathbf{a}_N(\phi_3) + \sqrt{\frac{1}{1+\varepsilon}} (\mathbf{h}_k^r)_0 \right), \quad (17)$$

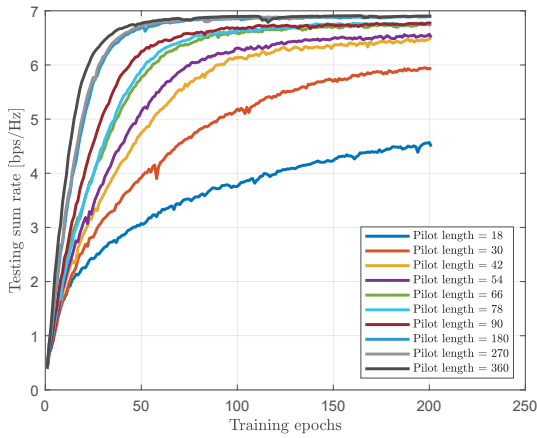
where $\mathbf{G}_0, (\mathbf{h}_k^r)_0$ are the non-line-of-sight components whose entries follow the distribution $\mathcal{CN}(0, 1)$, β_1 and $\beta_{2,k}$ are the corresponding path-losses, ε is the Rician factor which is set to be 10, \mathbf{a} is the steering vector, ϕ_1, ϕ_2 and ϕ_3 are the angular parameters. The path-loss of direct-link and cascaded-link are modeled as $32.6 + 36.7 \log(d_1)$ and $22 + 22 \log(d_2)$, respectively, where d_1, d_2 are the distance between users and the BS of the corresponding links [5]. The uplink and downlink transmission power are both set to be 15dBm, and the noise power of the uplink and the downlink are -100dBm and -85dBm respectively.

B. Neural Network Training and Testing

We consider a 3-layer $200 \times 200 \times 200$ neural network with ReLu non-linearity as the hidden layers of the proposed neural network. We implement the proposed network on TensorFlow and train the neural network using Adam optimizer with an initial learning rate 10^{-3} . At each training epoch, we iterate 100 times to update the parameters of the neural network, and 100 training samples are used to compute the gradients in each iteration.



(a) Sum rate v.s. pilot length.



(b) Testing sum rate v.s. training epochs.

Fig. 4. Performance of the proposed neural network.

In the testing stage, we compare the neural network with two benchmarks:

- **Perfect CSI+BCD (Benchmark 1):** Given perfect CSI, the sum-rate maximization problem is solved by the state-of-art block coordinate descent (BCD) algorithm proposed in [5]. We stop the BCD algorithm when the increase in sum rate between two consecutive iterations is below 10^{-3} .
- **LMMSE channel estimation + BCD (Benchmark 2):** We first estimate the channels using the LMMSE estimator developed in section III, then perform sum-rate maximization using the BCD algorithm [5]. The required statistics for the LMMSE estimator are computed from 10000 channel realizations.

C. Results

We first illustrate the impact of uplink pilot length on the system downlink sum rate in Fig. 4(a). The training of neural network is terminated after 200 training epochs, and the prediction of the beamforming matrix and phase shifts is evaluated on a testing set with 1000 samples. The sum

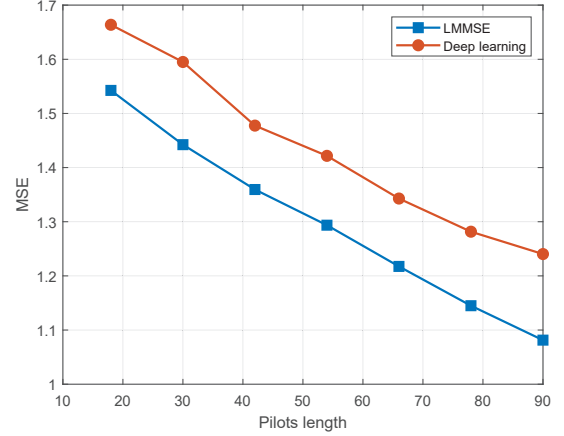


Fig. 5. MSE v.s. pilot length.

rate of two benchmarks are also averaged over 1000 channel realizations. From Fig. 4(a), the proposed deep learning approach outperforms Benchmark 2 when the pilot length is less than 200. Given 54 pilots, the deep learning approach only loses 6.7% sum rate compared with Benchmark 1 which assumes perfect CSI. The deep learning approach with 54 pilots still achieves better performance than the Benchmark 2 with 180 pilots, which shows a significant reduction of pilot overhead. Benchmark 2 can achieve approximately the same performance as Benchmark 1 when the pilot length is 360. This is because in noiseless case 303 pilot symbols are needed for perfect channel estimation, while 360 pilots is enough to achieve satisfying channel estimation quality in noisy case.

Next, we show how much data is needed to train the proposed neural network, in Fig. 4(b), we plot the sum rate evaluated on testing data against the training epochs. Recall that we sample 10000 training data in each training epoch. It can be seen from 4(b) that the sum rate converges faster as the pilot length increases. This is because when the pilot length is large, we have more information about the channel in one data sample, i.e., received pilots \mathbf{Y} .

D. Implicit vs. Explicit Channel Estimation

To understand the benefit of implicit channel estimation, we now implement a neural network for designing phase shifts and beamforming but based on explicit channel estimation scheme and compare its performance with the implicit channel estimation strategy proposed in this paper. Toward this end, we parameterize the MMSE estimator \mathbf{h} of problem (11) by a neural network of size $2\tau M \times 1000 \times 2M(N+1)$ with ReLu non-linearity. After 200 training epochs, i.e., using the same amount of data as the deep learning method in Fig. 4(a), the neural network for minimizing the mean squared error (MSE) is well trained. We compare the performance of the trained neural network for channel estimation with the LMMSE estimator by evaluating the MSE on 1000 testing samples in Fig. 5. It shows that the LMMSE actually achieves better performance than the trained neural network, which indicates that the expressive capacity of the constructed neural network

TABLE I
GENERALIZATION PERFORMANCE OF DEEP LEARNING APPROACH.

Location of users	Testing sum rate as % of Benchmark 1
(150m, 30m)	95.24
(130m, 30m)	94.90
(100m, 30m)	86.77

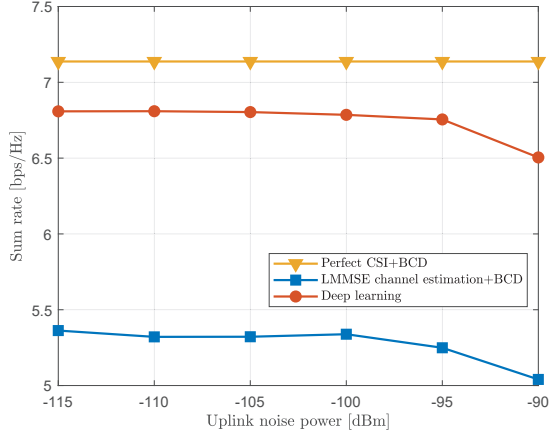


Fig. 6. Testing sum rate v.s. uplink noise power.

is not sufficient to achieve as good a mean squared error as the LMMSE estimator. However, it is observed in Fig. 4(a) that at this size, the neural network with end-to-end-training can already do better than the explicit channel estimation strategy in terms of sum rate. Combining these observations suggests that the neural network extracts more important information than the explicit estimation of the channel matrix $\hat{\mathbf{F}}_k$ from the received pilots for the design of the optimal phase shifts and beamforming matrix.

Note also that the dimension of the output of the neural network for solving the sum-rate maximization problem is much smaller than the output of the neural network needed for minimizing the MSE. This is another reason that it is advantageous to maximize the sum rate directly instead of recovering the entries of the channel matrix first.

E. Generalizability

To evaluate the generalization ability of the proposed deep learning method for sum-rate maximization, the trained neural network (in Fig. 4(a)) is tested on different testing sets, in which the center of the circular area of the users is changed from (150m, 30m) to (130m, 30m) and (100m, 30m). We fix the pilot length to be 90. The results in Table I show that the same trained neural network generalizes well if the change in environment is not too large.

In Fig. 6, we show the testing performance of the deep learning approach at different uplink noise power (as compared to the uplink noise power of -100dBm in the training phase). It can be observed that the performance of deep learning decreases with a trend similar to Benchmark 2, which illustrates that the proposed neural network generalizes well under different uplink noise power scenarios.

VI. CONCLUSION

Conventional communication system design always involves obtaining accurate CSI first, then designing the optimal transmission scheme according to the CSI. This design strategy is not practical for IRS due to the large number of passive reflective elements at the intelligent surface. This paper proposes an approach that learns to configure the IRS and the beamforming at the BS to maximize the system sum rate directly based on the received pilots, thereby bypassing the explicit channel estimation stage. This is accomplished by a neural network that unveils the direct mapping from the received pilots to the optimal configuration. Simulation results show that the trained neural network can efficiently learn to solve the sum-rate maximization problem using much fewer pilots compared with the channel estimation based approach.

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