Channel Estimation for RIS aided communication using Deep Learning

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***Abstract*—Reconfigurable Intelligent Surface (RIS) are a promising solution for improving wireless network capacity and coverage. Machine learning (ML) is an effective method for maximizing the possible advantages of RIS-assisted communication systems, particularly when the computational complexity of operating and deploying RIS increases rapidly as the number of interactions between the user and the infrastructure starts to grow. This report presents a Deep Learning (DL) framework for channel estimation in RIS assisted massive MIMO (multiple-input multiple-output) systems. The proposed framework uses a deep neural network to learn the mapping from input features to channel estimates, significantly reducing the computational complexity and improving estimation accuracy.**

***Index Terms*—Reconfigurable intelligent surface, Channel estimation, Deep learning, massive MIMO**

I. Introduction

Reconfigurable Intelligent Surfaces (RISs) have gained considerable attention from the wireless communication community due to their effectiveness, affordability, reconfigurability, ease of deployment and passive system modules that can be used to control the wireless propagation environment by electromagnetic wave re-engineering [5]. The manipulation of the propagation environment through RISs has been identified as a promising solution for the next generation of wireless technologies, including terahertz communications, non-orthogonal multiple access, and low-cost massive multiple-input multiple-output (MIMO) systems.

With the growing density of mobile users, the rapid increase in mobile data traffic flow, and a wide variety of services and applications, next-generation wireless networks need to adapt to high-frequency waves. However, these signals are obstructed by objects and diminish over long distances - signal attenuation (Friis formula). RISs addresses this issue by intelligently changing the wireless propagation environment and improve wireless network capacity and coverage. As a result, RISs are a potential technology for the sixth generation of communication networks.

A RIS is an electromagnetic 2-D surface that is composed of large number of passive reconfigurable reflecting elements which are fabricated from meta-materials [4]. RIS includes a programmable meta-surface which can be controlled via external signals such as backhaul control link [6], [8] from the base station (BS). Hence, real-time manipulation of the reflected phase and magnitude becomes possible. This property allows us to use RIS in wireless communications as a reflecting surface between the BS and the users to improve the received signal energy, expanding the coverage as well as reducing the interference [7]. While RIS can provide low-cost and simplistic architecture, it brings difficulty of including two wireless channels between the BS and the user, one being the direct channel and another one is the cascaded channel between the BS and the users through RIS.

II. Illustration

Consider a situation as shown in Fig. 1. By placing the RIS the signal coming through the window will reach RIS and from there the signal is reflected to the user. The main point is that even if the direct LOS is not present the signal reaches the user with the help of RIS.

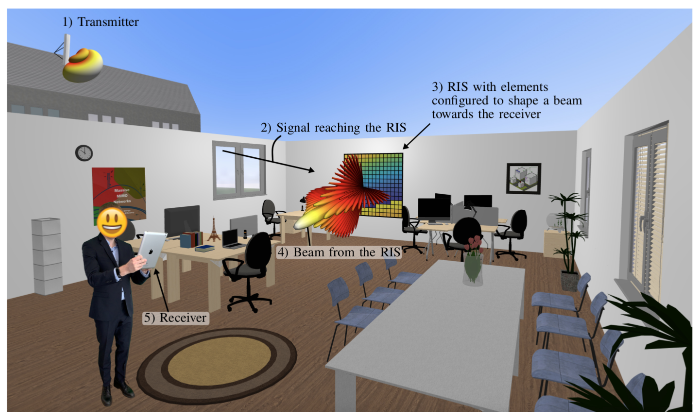

Fig. 1: Wireless propagation environment with RIS [1]

III. Application of Machine Learning in RIS

Machine learning has become an increasingly popular tool for optimizing wireless communication systems, and reconfigurable intelligent surfaces (RIS) are no exception. Machine learning algorithms can be used to automatically learn and adapt to the environment, allowing for efficient resource allocation and improved system performance.

One key application of machine learning in RIS is channel estimation. Traditional methods of estimating channel state information (CSI) can be computationally expensive and time-consuming, especially in large-scale MIMO systems. Machine learning approaches, such as deep neural networks, can learn the mapping from input features to channel estimates, significantly reducing the computational complexity and improving estimation accuracy. Another application of machine learning in RIS is beamforming optimization. Machine learning algorithms can be used to learn the optimal beamforming weights for RIS-aided systems, improving the signal-to-noise ratio and reducing interference. Reinforcement learning, in particular, has been shown to be effective in optimizing beamforming policies in RIS-aided systems. The Fig. 2 represents the various areas of RIS where Machine learning can be used.

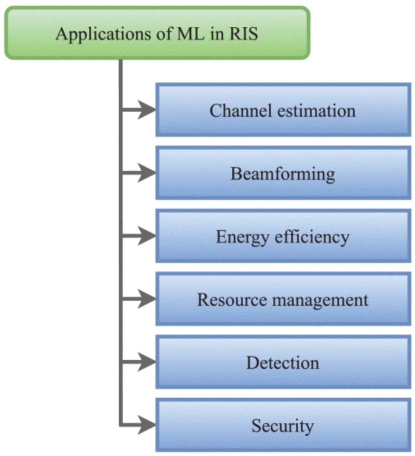

Fig. 2: Applications of ML in RIS [3]

In this paper, we explore about the deep learning method for channel estimation.

IV. System Model and Problem Formulation

Consider the system model as depicted in Fig. 3. Here, the Base station (BS) has M antennas to transmit to K single-antenna users with the assistance of RIS which is composed of L passive reflecting elements.

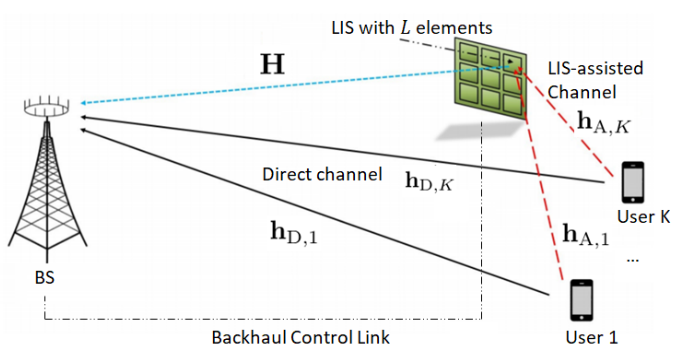

Fig. 3: RIS assisted mm-Wave massive MIMO scenario [2]

In RIS-assisted communication scheme, there are two channels

- **Direct Channel** is the Conventional communication between the base station and users.

$$\text{BS} \rightarrow \text{User}$$

- **Cascaded Channel** is the channel introduced by RIS.

$$\text{BS} \rightarrow \text{RIS} \rightarrow \text{User}$$

RIS can change the property of signal reflected, here in this paper we only discuss about the case where the RIS changes only phase of the signal i.e., Each RIS element introduces a phase shift onto the incoming signal from the BS. The phase of each RIS element can be adjusted through the PIN diodes which are controlled by the RIS-controller connected to the BS over the Backhaul Link (acts as a controller for RIS). The transmitted signal is received to the k-user with two components, one of which is through the direct path from the BS and the another one is through the RIS. The received signal from the k-th user can be given by

$$y_k = (\underbrace{\mathbf{h}_{\mathrm{D},k}^{\mathsf{H}}}_{Direct} + \underbrace{\mathbf{h}_{\mathrm{A},k}^{\mathsf{H}}\, \boldsymbol{\Psi}^{\mathsf{H}}\, \mathbf{H}^{\mathsf{H}}}_{Cascaded})\, \overline{\mathbf{x}} + n_k \tag{1}$$

where n_k is the noise - $n_k \sim \mathcal{CN}(0, \sigma_n^2)$ and $\mathbf{h}_{\mathrm{D},k}, \mathbf{h}_{\mathrm{A},k}$ represents the channel between k-th user, Base station and k-th user, RIS respectively. $\mathbf{H}$ denotes the channel between BS and RIS. Note that $\mathbf{h}_{\mathrm{D},k} \in \mathbb{C}^M, \mathbf{h}_{\mathrm{A},k} \in \mathbb{C}^L, \mathbf{H} \in \mathbb{C}^{M \times L}$
The matrix $\boldsymbol{\Psi}$ dentoes the phase shift caused to the signal by each of the L RIS elements, $\boldsymbol{\Psi} \in \mathbb{C}^{L \times L}$ is a diagonal matrix.

$$\boldsymbol{\Psi} = \mathrm{diag}\{\beta_1 \exp(j\phi_1), \ldots, \beta_L \exp(j\phi_L)\} \tag{2}$$

Here, $\beta_l \in \{0, 1\}$ represents the on/off state of the RIS elements. $\phi_l \in [0, 2\pi)$ is the phase shift of the reflective elements. Let $\mathbf{G}_k \in \mathbb{C}^{M \times L}$ be the cascaded channel matrix between the BS and the k-th user as $\mathbf{G}_k = \mathbf{H}\boldsymbol{\Gamma}_k$ where $\boldsymbol{\Gamma}_k = \mathrm{diag}\{\mathbf{h}_{\mathrm{A},k}\}$. Then, we can write $\mathbf{H}\boldsymbol{\Psi}\mathbf{h}_{\mathrm{A},k} = \mathbf{G}_k\psi$, for which we have $\boldsymbol{\Psi} = \mathrm{diag}\{\psi\}$. Then using these notation we get the following equation

$$y_k = (\mathbf{h}_{\mathrm{D},k}^{\mathsf{H}} + \psi^{\mathsf{H}}\mathbf{G}_k^{\mathsf{H}})\,\mathbf{x} + n_k \tag{3}$$

The aim is to estimate the direct and cascaded channels $\{\mathbf{h}_{\mathrm{D},k}, \mathbf{G}_k\}$ in downlink transmission. In this case, we assume that each user feeds the received pilot signals to the deep network to estimate its own channel.

V. Saleh-Valenzuela (SV) Model

The SV model is a geometric modelling of a channel. The SV model characterizes the wireless channel as a combination of multiple propagation paths, each with different attenuation, delay and phase characteristics

Using the SV method authors assumed that the mm-Wave channels, i.e., $\mathbf{h}_{\mathrm{D},k}, \mathbf{h}_{\mathrm{A},k}$ and $\mathbf{H}$ include the contributions of N_D, N_A and N_H paths respectively. Thus, the channels $\mathbf{h}_{\mathrm{D},k}$ and $\mathbf{h}_{\mathrm{A},k}$ can be represented as,

$$\mathbf{h}_{\mathrm{D},k} = \sqrt{\frac{M}{N_{\mathrm{D}}}} \sum_{n_{\mathrm{D}}=1}^{N_{\mathrm{D}}} \alpha_{\mathrm{D},k}^{(n_{\mathrm{D}})}\, \mathbf{a}_{\mathrm{D}}(\theta_{\mathrm{D},k}^{(n_{\mathrm{D}})}) \tag{4}$$

$$\mathbf{h}_{\mathrm{A},k} = \sqrt{\frac{L}{N_{\mathrm{A}}}} \sum_{n_{\mathrm{A}}=1}^{N_{\mathrm{A}}} \alpha_{\mathrm{A},k}^{(n_{\mathrm{A}})}\, \mathbf{a}_{\mathrm{A}}(\theta_{\mathrm{A},k}^{(n_{\mathrm{A}})}) \tag{5}$$

where $\{\alpha_{\mathrm{D},k}, \alpha_{\mathrm{A},k}\}$ and $\{\theta_{\mathrm{D},k}^{(n_{\mathrm{D}})}, \theta_{\mathrm{A},k}^{(n_{\mathrm{A}})}\}$ are the complex channel gains and received path angles for the corresponding channels, respectively. $\mathbf{a}_{\mathrm{D}}(\theta)$ and $\mathbf{a}_{\mathrm{A}}(\theta)$ are $M\times 1$ and $L\times 1$ steering vectors of the path angles.

$$\mathbf{a}_{\mathrm{D}}(\theta) = \frac{1}{\sqrt{M}}[e^{j\omega_0}, \ldots, e^{j\omega_{M-1}}]^{\top} \tag{6}$$

$$\mathbf{a}_{\mathrm{A}}(\theta) = \frac{1}{\sqrt{M}}[e^{j\omega_0}, \ldots, e^{j\omega_{L-1}}]^{\top} \tag{7}$$

where $\omega_n = n\frac{2\pi d}{\lambda}\pi\sin(\theta)$ and $d = \frac{\lambda}{2}$ is the array spacing for wavelength λ. The channel between the BS and RIS is represented as,

$$\mathbf{H} = \sqrt{\frac{ML}{N_{\mathrm{H}}}}\sum_{n_{\mathrm{H}}=1}^{N_{\mathrm{H}}}\alpha^{(n_{\mathrm{H}})}\,\mathbf{a}_{\mathrm{BS}}(\theta_{\mathrm{BS}}^{(n_{\mathrm{H}})})\,\mathbf{a}_{\mathrm{RIS}}^{\mathrm{H}}(\theta_{\mathrm{RIS}}^{(n_H)}) \tag{8}$$

where $\alpha^{(n_{\mathrm{H}})} \in \mathbb{C}$ denotes the complex gain and $\{\theta_{\mathrm{BS}}^{(n_{\mathrm{H}})}, \theta_{\mathrm{RIS}}^{(n_H)}\}$ are the angle of departure and angle of arrival angles of the paths respectively. $\mathbf{a}_{\mathrm{BS}}(\theta) \in \mathbb{C}^M$ and $\mathbf{a}_{\mathrm{RIS}}(\theta) \in \mathbb{C}^L$ are the steering vectors.

VI. Channel Estimation using Deep Learning

A. Training Data

The SV channel model is used to generate the training data for the deep learning model. This would allow the deep learning model to learn the statistical properties of the wireless channel, including the effects of multipath propagation caused by reflections, diffractions, and scattering from the physical environment. We model the channel and generate the data - input and output, this is used to train the DL model

B. Labelling

We first begin training the model by identifying the "labels" (for training purpose). Consider the downlink scenario where the BS transmits signals $\mathbf{x}_p \in \mathbb{C}^M$, with τ , with $p = 1, \ldots, P$ and $P \geq M$. Hence, the total number of channel uses to estimate the direct channel is P The received signal at the k-th user can be given by

$$\mathbf{y}_k = \left(\mathbf{h}_{\mathrm{D},k}^{\mathsf{H}} + \psi^{\mathsf{H}}\mathbf{G}_k^{\mathsf{H}}\right)\mathbf{X} + \mathbf{n}_k \tag{9}$$

where $\mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_P] \in \mathbf{C}^{M\times P}$ is the transmitted signal matrix and $\mathbf{y}_k = [y_{k,1}, \ldots, y_{k,P}]$ is the received signal matrix both are $1\times P$ row vectors and $\mathbf{n}_k \sim \mathcal{CN}\left(0, \sigma_n^2\mathbf{I}_P\right)$.

We divide the pilot training has two phases:

- Phase 1: Direct Channel Estimation ($\mathbf{h}_{\mathrm{D},k}$) - In this phase, we assume that all of the LIS elements are turned off, i.e., $\beta_l = 0, \forall l$, by using the BS backhaul link. Then, the received baseband signal at the k-th user becomes

$$\mathbf{y}_{\mathrm{D}}^{(k)} = \mathbf{h}_{\mathrm{D},k}^{\mathsf{H}}\mathbf{X} + \mathbf{n}_{\mathrm{D},k} \tag{10}$$

  As we ignore the cascaded channel coefficients we are left only with direct channel and we first train the model on this. Now the direct channel $\mathbf{h}_{\mathrm{D},k}$ is considered as the label for the corresponding input data $\mathbf{y}_{\mathrm{D}}^{(k)}$

- Phase 2: Cascaded Channel Estimation ($\mathbf{G}_k$) - After obtaining the direct channel coefficients, In this phase we obtain the cascaded channel coefficients

$$\mathbf{y}_{\mathrm{C}}^{(k,l)} = \left(\mathbf{h}_{\mathrm{D},k}^{\mathrm{H}} + \mathbf{g}_{k,l}^{\mathrm{H}}\right)\mathbf{X} + \mathbf{n}_{k,l} \tag{11}$$

C. Proposed Model - ChannelNet

The model is implemented from the above equations and the algorithm 1 using MATLAB's DeepLearning Toolbox and tuned hyperparameters as given in the paper [2]. The pseudocode for the algorithm is given in [2] and the same has been implemented.

Algorithm 1 Training data generation for ChannelNet.

Input: K, U, V, $\mathbf{X}$, $\boldsymbol{\psi}$ SNR, $\mathrm{SNR}_{\mathbf{h}}$, $\mathrm{SNR}_{\mathbf{G}}$.
Output: Training datasets $\mathcal{D}_{\mathrm{DC}}$ and $\mathcal{D}_{\mathrm{CC}}$.
Initialize with $t = 1$ and the dataset length is $T = UVK$.
for $1 \leq v \leq V$ **do**
    Generate $\mathbf{h}_{\mathrm{D},k}^{(v)}$ and $\mathbf{G}_k^{(v)}$ from Section IV , $\forall k$.
    for $1 \leq u \leq U$ **do**
    $[\mathbf{h}_{\mathrm{D},k}^{(u,v)}]_{i,j} \sim \mathcal{CN}([\mathbf{h}_{\mathrm{D},k}^{(v)}]_{i,j}, \sigma_{\mathbf{h}}^2)$, $\forall k$.
    $[\mathbf{G}_k^{(u,v)}]_{i,j} \sim \mathcal{CN}([\mathbf{G}_k^{(v)}]_{i,j}, \sigma_{\mathbf{G}}^2)$, $\forall k$.
    for $1 \leq k \leq K$ **do**
    Using $\mathbf{h}_{\mathrm{D},k}^{(u,v)}$ and $\mathbf{g}_{k,l}^{(u,v)}$, generate $\mathbf{y}_{\mathrm{D}}^{(k)^{(u,v)}}$ and $\mathbf{y}_{\mathrm{C}}^{(k,l)^{(u,v)}}$ from (10) and (11).
    Using $\mathbf{y}_{\mathrm{D}}^{(k)^{(u,v)}}$ and $\mathbf{y}_{\mathrm{C}}^{(k,l)^{(u,v)}}$; design $\mathbf{X}_{\mathrm{DC}}^{(t)}$ and $\mathbf{X}_{\mathrm{CC}}^{(t)}$.
    Using $\mathbf{h}_{\mathrm{D},k}^{(u,v)}$, $\mathbf{G}_k^{(u,v)}$; design the output $\mathbf{z}_{\mathrm{DC}}^{(t)}$, $\mathbf{z}_{\mathrm{CC}}^{(t)}$.
    $\mathcal{D}_{\mathrm{DC}}^{(t)} = (\mathbf{X}_{\mathrm{DC}}^{(t)}, \mathbf{z}_{\mathrm{DC}}^{(t)})$, $\mathcal{D}_{\mathrm{CC}}^{(t)} = (\mathbf{X}_{\mathrm{CC}}^{(t)}, \mathbf{z}_{\mathrm{CC}}^{(t)})$.
    $t \leftarrow t + 1$,
    end for k,
    end for u,
end for v,

The proposed "ChannelNet" architecture is depicted in Fig. 4. In [2] the authors use a three-channel model which utilizes both the real and imaginary values to improve the performance by enriching the features extracted from the input data. This can be related to Image processing, as typically CNNs are used there and also an image is generally a 3 channel signal.

Suppose y is the received pilot, it is then divided as appropriate sub vectors as follows For the first and the second channels of $\mathbf{X}_{\mathrm{DC}}$, we have $\mathrm{vec}\{[\mathbf{X}_{\mathrm{DC}}]_1\} = \mathrm{Re}\{\mathbf{y}_{\mathrm{D}}^{(k)}\}$ and $\mathrm{vec}\{[\mathbf{X}_{\mathrm{DC}}]_2\} = \mathrm{Im}\{\mathbf{y}_{\mathrm{D}}^{(k)}\}$. The third channel is denoted by the element-wise absolute value of $\mathbf{y}_{\mathrm{D}}^{(k)}$ as $\mathrm{vec}\{[\mathbf{X}_{\mathrm{DC}}]_3\} = |\mathbf{y}_{\mathrm{D}}^{(k)}|$. The assumption is that the real and imaginary parts of y as in phase and quadrature parts.

VII. Training Results

The training results of the channel net with the parameters given in the paper is depicted in Table I

Epoch	Iteration	Mini-batch RMSE	Validation RMSE	Mini-batch loss	Validation Loss	Base Learning Rate
1	1	104.54	100.70	5464.3315	5070.5103	2.1100e-06
19	50	35.45	38.49	628.3396	740.5687	2.1100e-06
17	100	21.57	23.13	232.6245	267.5727	6.3300e-07
25	150	17.95	19.73	161.0625	194.6484	1.8990e-07
34	200	17.59	18.71	154.6587	175.1135	5.6970e-08

Table I: Validation Loss at each Stage

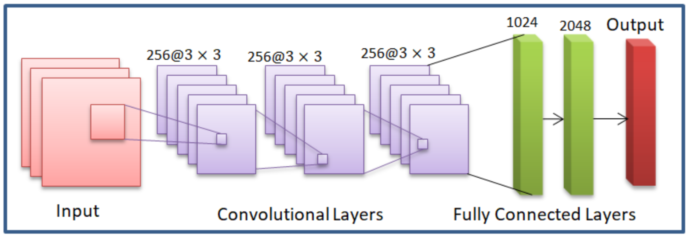

Fig. 4: Deep Neural network Architecture

VIII. Metrics and Plots

The metric used is Normalized Mean Square Error. NMSE for $\mathbf{G}_k$ is defined as

$$\mathrm{NMSE}\,(G_k) = \frac{1}{J}\sum_{j=1}^{J} ||\mathbf{G}_k - \hat{\mathbf{G}}_k^{(j)}||_{\mathcal{F}}/||\mathbf{G}_k||_{\mathcal{F}} \tag{12}$$

The plot of NMSE vs SNR of our implementation of ChannelNet is depicted in Fig. 5. The plot is a combination of both the cascaded channel and direct channel for the output. A similar plot is obtained as in [2]

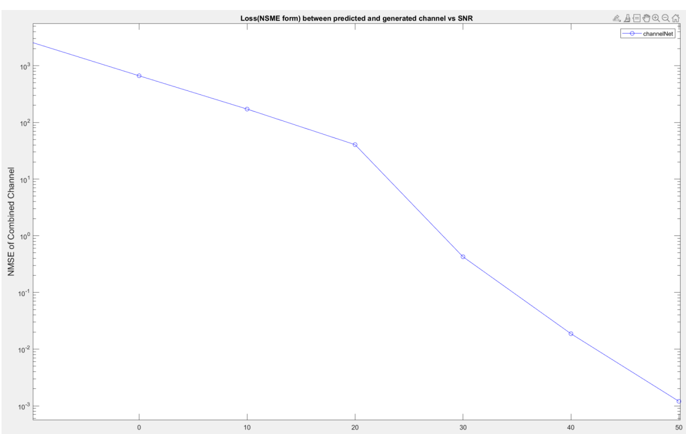

Fig. 5: NMSE vs SNR

IX. Further Research and Exploration

Through this project we have demonstrated that Deep Learning models are a promising approach for channel estimation in RIS-controlled environments. There is a lot of work being done in this field. Many uses of Deep Learning, Federated Learning, and Reinforcement Learning are under development to further improve prediction accuracy. The research paper [3] depicts a review of all Machine learning methods that can be used for RIS aided communication.

References

[1] Emil Björnson, Özgecan Özdogan, and Erik G. Larsson. Reconfigurable intelligent surfaces: Three myths and two critical questions. *CoRR*, abs/2006.03377, 2020.

[2] Ahmet M. Elbir, Anastasios Papazafeiropoulos, Pandelis Kourtessis, and Symeon Chatzinotas. Deep channel learning for large intelligent surfaces aided mm-wave massive mimo systems. *IEEE Wireless Communications Letters*, 9(9):1447–1451, 2020.

[3] K. M. Faisal and Wooyeol Choi. Machine learning approaches for reconfigurable intelligent surfaces: A survey. *IEEE Access*, 10:27343–27367, 2022.

[4] Chongwen Huang, Alessio Zappone, George C. Alexandropoulos, Mérouane Debbah, and Chau Yuen. Reconfigurable intelligent surfaces for energy efficiency in wireless communication. *IEEE Transactions on Wireless Communications*, 18(8):4157–4170, 2019.

[5] Aymen Khaleel and Ertugrul Basar. Reconfigurable intelligent surface-empowered mimo systems. *IEEE Systems Journal*, 15(3):4358–4366, 2021.

[6] Junliang Lin, Gongpu Wang, Rongfei Fan, Theodoros A. Tsiftsis, and Chintha Tellambura. Channel estimation for wireless communication systems assisted by large intelligent surfaces, 2019.

[7] Wankai Tang, Jun Yan Dai, Ming Zheng Chen, Kai-Kit Wong, Xiao Li, Xinsheng Zhao, Shi Jin, Qiang Cheng, and Tie Jun Cui. Mimo transmission through reconfigurable intelligent surface: System design, analysis, and implementation. *IEEE Journal on Selected Areas in Communications*, 38(11):2683–2699, 2020.

[8] Zhaorui Wang, Liang Liu, and Shuguang Cui. Channel estimation for intelligent reflecting surface assisted multiuser communications: Framework, algorithms, and analysis, 2020.