# DEEP LEARNING BASED RIS AIDED I2V COMMUNICATION

Ayush Madhan Sohini+, Tathagat Pal+, Mohd. Hamza Naim Shaikh+, Vivek Ashok Bohara+

+Indraprastha Institute of Information Technology, Delhi, New Delhi, India, 110020
Email: {ayush19156, tathagat19211, hamzan, vivek.b,}@iiitd.ac.in

**With the advent of 5G and beyond, the wireless communication industry is rapidly evolving, which has led to the development in various fields such as the internet of things (IoT), vehicle-to-vehicle (V2V), vehicle-to-everything (V2X) etc. The advancements in technology that support higher bandwidth have resulted in a massive boom in the number of devices operating in the same spectrum, resulting in significant interference. An effective solution to tackle this problem is the use of reconfigurable intelligent surface (RIS). RIS is a promising solution to build a programmable wireless environment via steering the incident signal in fully customizable ways with reconfigurable passive elements. Our project aims at optimizing the phase shift matrix and the power allocation in a V2X framework assisted by RIS. We plan to develop a dual optimization problem that tackles the mentioned problem. We intend to propose an optimal solution by training a deep neural network considering the weighted sum rate as a performance evaluation metric.**

***Index Terms*—Reconfigurable intelligent surfaces (RIS), infrastructure to vehicle (I2V), device to device (D2D), multiple-input-multiple-output (MIMO).**

## I. INTRODUCTION

Reconfigurable intelligent surfaces (RIS) is an artificial structure consisting of passive radio elements, each of which could adjust the reflection of the incident electromagnetic waves with unnatural properties [1]–[7]. Moreover, owing to the passive structure, the power consumption is extremely low, and there is nearly no additional thermal noise added during reflecting. As a result, the RIS attracts more and more attentions in academia and industry with vast applica- tion prospect, e.g., wireless power transfer [8], [9], physical layer security [10]–[12], cognitive radio network [13], etc. Among them, one of the most promising applications is to improve the quality-of-service of users in the wireless communication system suffering from unfavorable propagation conditions [14]–[18]. In this paper, we investigate the RIS-aided multiple-input single-output (MISO) multiuser downlink communication system as shown in Fig. 1, in which a multi-antenna access point (AP) serves multiple single-antenna mobile users. The direct links between the AP and the mobile users may suffer from deep fading and shadowing, and the RIS improves the propagation conditions by providing high- quality virtual links from the AP to the users. While RIS resembles a full-duplex amplify-and-forward relay [19], [20], it forwards the RF signals via passive reflection, and thus has advantages in both energy- and cost- efficiency. The objective of this paper is to maximize the weighted sum- rate (WSR) of the mobile users by jointly optimizing the beamforming at the AP and the phase coefficients of the RIS elements.

## II. RELATED WORK

The system in this paper has already investigated by some early-attempt works, in which different objectives are considered while most works assume that the perfect channel state information (CSI) of all involved channels is available. In [21] and [22], the transmit power of the AP is minimized by decomposing the joint optimization problem into two subproblems: one is the conventional power-minimization problem in MIMO system, and the other is for the RIS phase vector optimization. Then the phase optimization problem is solved via semidefinite relaxation (SDR) technique. Although this alternating optimization approach achieves quite good performance, the main shortcoming is that the proposed algorithm cannot obtain the stationary solution, and the complexity is a little high especially for large-size RIS. In [23] and [24], the energy efficiency is maximized, while employing zero-forcing (ZF) precoding at the AP. Since the ZF precoding completely cancels the inter- user interference, the power allocation at the AP and the phase optimization at RIS can be well decoupled. However, the ZF precoding may as well amplify the background noise, and the performance may be severely compromised when the channel is ill-conditioned. Unfortunately, the derivations in [24] are not applicable directly for other precoding schemes. Another important issue for the RIS-aided system is the channel estimation. It is known from [20]–[24] that, to optimize the phase vector of the RIS, the system needs high-accuracy CSI about the AP-RIS channel and the RIS-user channels, respectively. However, to obtain perfect CSI is not always possible, since the RIS is passive without channel sensing capability in typical setup. This challenge has been addressed by [25] and [26] via exploiting statistical CSI. Specifically, the single user system is investigated in [25], and the average received SNR is maximized while assuming that the line-of-sight (LoS) component of the channel is known. In [26], multiuser system is considered in which all the users are located in the same cluster whose spatial correlation relation is known by the system. Then, the max- min fairness problem is investigated by means of large dimensional random matrix theory. However, the performance of these methods in [25] and [26] depends heavily on the channel model assumptions, as well as the objective functions investigated.

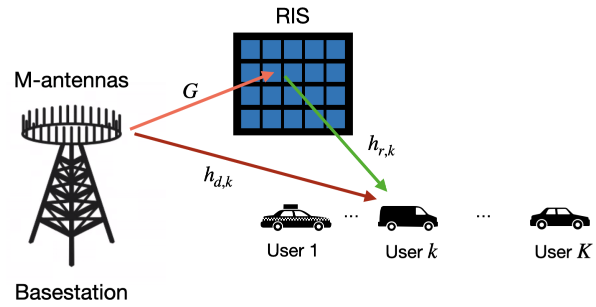



Fig. 1. System Model

## III. Contributions

Our project aims at optimizing the phase shift matrix and the power allocation in a V2X framework assisted by RIS. We plan to develop a dual optimization problem that tackles the mentioned problem. First we analyse an existing solution proposed in [27] that introduces an algorithm that iteratively breaks the non-convex optimization function to sub optimal convex functions. Our novelty is introduced in the DNN architecture. We intend to propose an optimal solution by training a deep neural network considering the weighted sum rate as a performance evaluation metric(loss function).

## IV. System Model

The channels from basestation (BS) to user $k$, from BS to RIS, and from RIS to user $k$ are denoted by $\mathbf{h}_{d,k} \in C^{M\times 1}$, $\mathbf{G} \in C^{N\times M}$, and $\mathbf{h}_{r,k} \in C^{N\times 1}$, respectively. We assume that all the channels experience quasi-static flat-fading and follow path-loss model. The phase-shift matrix is defined as a diagonal matrix $\Theta = diag(\theta_1, ...\theta_n, ...\theta_N)$, where $\theta_n = e^{j\psi_n}$ is the phase of the $n^{th}$ reflection element. Defining $H_{r,k}$ as $diag(\mathbf{h}^H_{r,k})\mathbf{G}$

SINR at the $k^{th}$ user is given as:

$$\gamma_k = \frac{|(\mathbf{h}^{\mathbf{H}}_{d,k} + \boldsymbol{\theta}^H \mathbf{H}_{r,k})\mathbf{w}_k|^2}{\sum_{i=1,i\neq k}^{K} |(\mathbf{h}^H_{d,k} + \boldsymbol{\theta}^H \mathbf{H}_{r,k})\mathbf{w}_i|^2 + \sigma_o^2} \tag{1}$$

Throughput, $\tau$ is given as:

$$\tau = \sum_{k=1}^{K} \mathbf{w}_k log(1+\gamma_k) \tag{2}$$

In addition, the transmit power constraint of BS is:

$$\sum_{k=1}^{K} \|\mathbf{w}_k\|^2 \leq P_T \tag{3}$$

### A. Analytical Model

The Closed Form Fractional Programming Approach was proposed in [] to deal with the sum-of-logarithms-of-ratio problem as follows:

$$\max_x \sum_{k=1}^{K} \log\left(1 + \frac{|A_k(\mathbf{x})|}{B_k(\mathbf{x}) - |A_k(\mathbf{x})|^2}\right) \tag{4}$$

where $B_k(\mathbf{x}) > |A_k(\mathbf{x})|^2$ for all $k$. The closed form FP approach has two steps:

*1) Lagrangian Dual Transform:*

By introducing an auxiliary variable $\alpha_k$, the logarithm function can be tackled based on the following equation:

$$\log(1+\gamma_k) = \max_{\alpha_k \geq 0} \log(1+\alpha_k) - \alpha_k + \frac{(1+\alpha_k)\gamma_k}{1+\gamma_k} \qquad \textbf{s.t. } \alpha_k \geq 0, \forall k = 1, ..., k, \tag{5}$$

where $\alpha = [\alpha_1, \alpha_2, ..., \alpha_K]^T$.

*2) Quadratic Transformation:*

Given $\alpha$, one may focus on the following sum-of-ratios problem:

$$\max_{\mathbf{x}} \sum_{k=1}^{K} \frac{|A_k(\mathbf{x}|^2}{B_k\mathbf{x}} \tag{6}$$

The key idea is introducing auxiliary variables $\beta = [\beta_1, ..., \beta_k]^T$, and then the above problem is equivalently translated to:

$$\max_{\mathbf{x},\beta} \sum_{k=1}^{K} \Big(2Re\{\beta_k^* A_k(\mathbf{x}) - |\beta_k|^2 B_k(\mathbf{x})\}\Big). \tag{7}$$

The equivalence can be verified by substituting $\beta_k = \frac{A_k(x)}{B_k(x)}$ into above problem.

*3) Non-convex BCD:*

The BCD is an iterative method, where $\alpha$, $\beta$, , and $\theta$ are cyclically updated. To be specific, denote by $\bar{\alpha}$ , $\bar{\beta}$ , $\bar{W}$, and $\bar{\theta}$ the temporal optimization results in last iteration. Then, it is easy to carry out:

$$\alpha_k = \frac{\bar{\zeta}_k^2 + \bar{\zeta}_k\sqrt{\bar{\zeta}_k^2 + 4}}{2}, \tag{8}$$

$$\beta_k = \frac{\sqrt{\omega_k(1+\bar{\alpha_k})}(\mathbf{h}^H_{d,k} + \bar{\theta}^H \mathbf{H}_{r,k})_k}{\sum_{i=1}^{K} |(\mathbf{h}^H_{d,k} + \bar{\theta}^H \mathbf{H}_{r,k})\bar{w}_i|^2 + \sigma_o^2}, \tag{9}$$

$$\bar{\zeta}_k = \frac{1}{\sqrt{\omega_k}} Re\{\bar{\beta}_k^* \bar{h}_k^H \bar{w}_k\}, \tag{10}$$

$$\bar{\mathbf{h}}_k = \bar{\mathbf{h}}_{d,k} + \mathbf{H}^H_{r,k}\bar{\theta}. \tag{11}$$

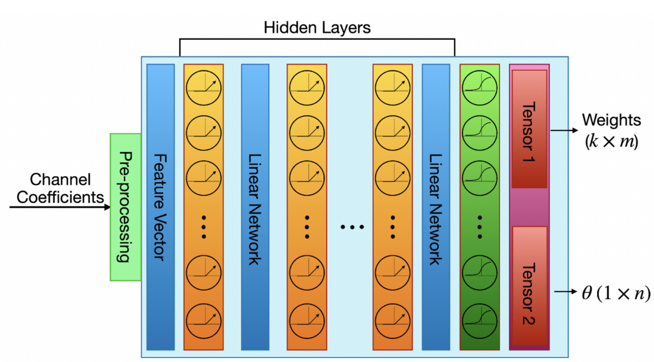
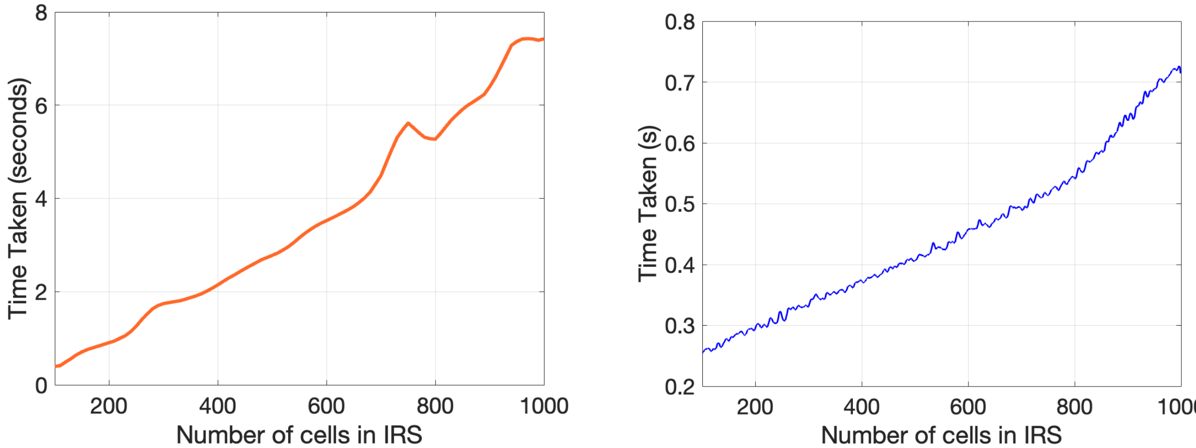



Fig. 2. The proposed NN architecture: IRS-Net.




(a) Time taken for the computation of the simulation mathematical model v/s epochs.

(b) Time taken for the computation of the DNN model v/s epochs

Fig. 3. Computational time comparison.

*4) Prox-Linear Update for Beamforming Vector:* **W**:

$$\mathbf{W} = arg \min_{\mathbf{W}} \sum_{k=1}^{K} \left( Re\{\mathbf{g}_k^H(\mathbf{w}_k - \hat{\mathbf{w}}_k)\} + \frac{L}{2}\|\mathbf{w}_k - \hat{\mathbf{w}}_k\|^2 \right) \quad \textbf{s.t.} \sum \|\mathbf{w}_k\|^2 \leq P_T, \tag{12}$$

where $L > 0$, the gradient is denoted by:

$$\mathbf{g}_k = -2\sqrt{\omega_k(1+\bar{\alpha}_k)}\bar{\beta}_k\bar{\mathbf{h}}_k + 2\sum_{i=1} K|\bar{\beta}_i|^2\bar{\mathbf{h}}_i\bar{\mathbf{h}}_i^H\hat{\mathbf{w}}_k, \tag{13}$$

We set $L = 2\|\sum_{i=1}^{K}|\bar{\beta}_i|^2\bar{\mathbf{h}}_i\bar{\mathbf{h}}_i^H\|_F$ which is the Lipschitz constant of the gradient $\mathbf{g}_k$.

*5) Successive Convex Approximation for Updating $\theta$*

$$U = \sum_{k=1}^{K}|\bar{\beta}_k|^2\sum_{i=1}^{K}\bar{a}_{i,k}\bar{a}_{i,k}^H \tag{14}$$

$$v = \sum_{k=1}^{K}\left(\sqrt{\omega_k(1+\bar{\alpha}_k)}\bar{\beta}_k^*\bar{a}_{k,k} - \bar{\beta}_k|^2\sum_{k=1}^{K}\bar{b}_{i,k}^*\bar{a}_{i,k}\right) \tag{15}$$

with $\bar{a}_{i,k} = \sum_{i=1}^{K}\mathbf{H}_{r,k}\bar{w}_i$ and $\bar{b}_{i,k} = \sum_{i=1}^{K}\mathbf{h}_{d,k}^H\bar{w}_i$. We further replace $\theta_n$ by $\phi_n$, where $\theta_n = e^{j\psi_n}$ and $\psi_n \in \mathbb{R}$. Then update rule is recast to:

$$arg\, min_{\psi\in\mathbb{R}^N} f^*(\psi) \triangleq (e^{j\psi})^H U e^{j\psi} - 2Re\{v^H e^{j\psi}\}. \tag{16}$$

$$\psi = \psi - \frac{\nabla f^*(\psi)}{\delta}. \tag{17}$$

$$\nabla f^*(\psi) = 2Re\{-je^{-j\psi} \circ (Ue^{j\psi} - v)\}. \tag{18}$$

Using Armijo rule, $\delta$ to determine step size:

$$\nabla f^*(\bar{\psi}) - \nabla f^*(\psi) \geq \delta\|\nabla f^*(\bar{\psi})\|^2 \tag{19}$$

### *B. Deep Neural Network*

We leverage DL theory to find high-quality sub-optimal solution of P. More specifically, we train the NN in an unsupervised manner. To this end, we propose an appropriate feature design, customized loss function and an NN architecture as shown in Fig. 2. Further details of our proposed approach are given in the following sub-sections.

*1) Feature Design:* The first step is to pre-process all the channel coefficients and design a suitable feature vector **f**. We exploit an inherent product structure of channel coefficients corresponding to each reflecting element and transmit antenna. Given *loss* is a concave function, we obtain a suboptimal solution. We concatenate vector $h_{df} \star h_{rk}$ into one vector with real and imaginary components of complex numbers.

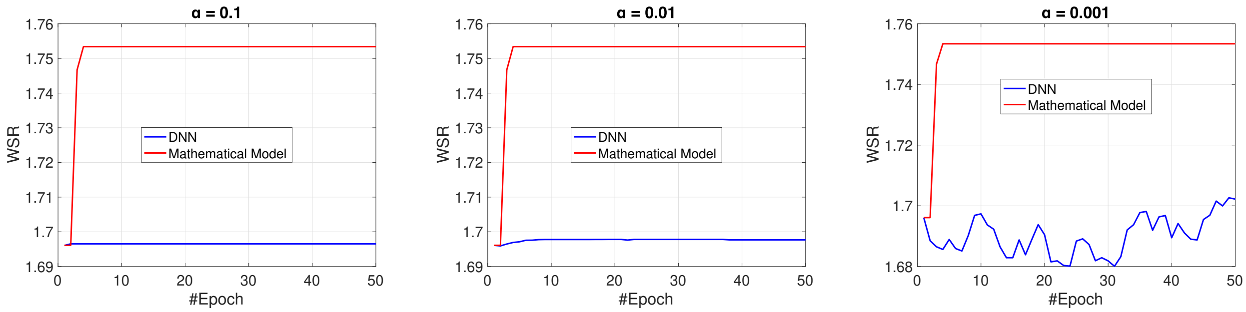
*2) Loss Function:* We exploit the closed-form equation for throughput i.e., to define a loss function $L$. The loss function is given as:

$$L = -\frac{1}{K^2}\sum_{k=1}^{K} w_k log(1+\gamma_k) \tag{20}$$

*3) Neural Network Architecture and Training:* *[Input] $\rightarrow$ [1028, 640, 320] $\rightarrow$ [Weights and $\theta$]*. We use the Adam optimizer with the learning rate, $\alpha = 0.01$. Each hidden layer consists of ReLU. Output layer consists of a sigmoid activation function. Sigmoid activation function inherently satisfies the unit magnitude constraints of phase shifts.

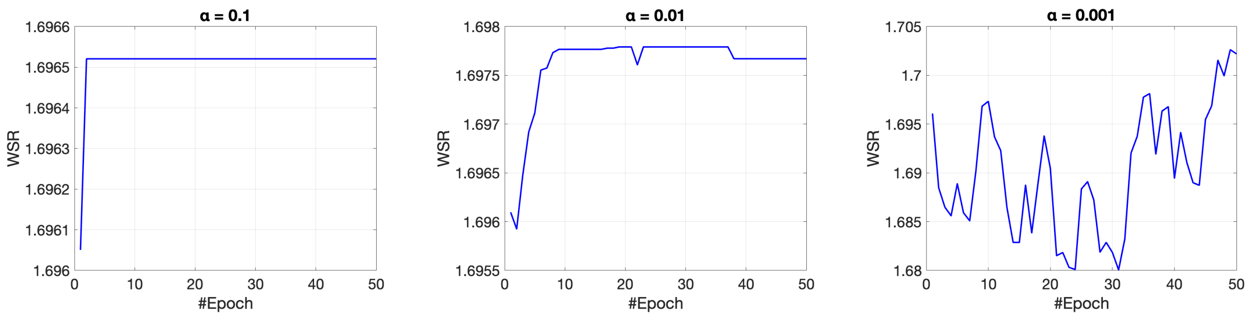
## V. Results

In this section, we present the results obtained using the mathematical and the DNN models described in the above sections. For fairness comparison, the weights are first chosen inversely proportional to the direct-link path-loss, and then normalized $\sum w_k = 1$. All the simulation curves have been averaged over 2000 independent realizations of channel small scale fading.




(a) $\alpha = 0.1$ (b) $\alpha = 0.01$ (c) $\alpha = 0.001$

Fig. 4. Weighted sum rate v/s Epochs for DNN and Mathematical simulation model.




(a) $\alpha = 0.1$ (b) $\alpha = 0.01$ (c) $\alpha = 0.001$

Fig. 5. Effect of $\alpha$ on Weighted sum rate.

In Fig. 4, the throughput is seen to be increasing with increasing number of iterations, until it converges. Each iteration consists of optimizing the $\psi$, $\alpha$, $\beta$ and $W$. It is evident that the values of the weighted sum rate (WSR) obtained using the mathematical simulation model is more than that of the WSR's generated using DNN. This is because the objective is concave minimization and the optimizer tends to find the nearest local optimal solution in every iteration. Gain in throughput minimal as compared to the mathematical simulation model.

Further, we analyze the impact of learning rate, $\alpha$ on the WSR obtained using DNN. In Fig. 5(a), when $\alpha = 0.1$, it finds the nearest local optimum very fast and stays there. Hence, the quick convergence occurs which results in a very suboptimal solution. For $\alpha = 0.01$, it converges at a higher value of epoch, but it gives the highest value of WSR. Lastly, for $\alpha = 0.001$, the LR is so small that the NN tries to find the nearest local optimum due to the presence of multiple local optima. We can see that the plot never converges. Thus, $\alpha = 0.01$ gives the best results.

In Fig. 3, we present the comparison of the time required to compute the WSR using mathematical simulation and the DNN model for varying number of number of cells in RIS. For number of cells, $N = 200$, the mathematical model requires around 1 second to run the 50 iterations. Whereas, the DNN model is able to compute this in just 0.3 seconds. Similarly, for $N = 1000$, the mathematical model requires around 8 seconds, but the DNN is achieving the same task in only 0.7 seconds. In both the scenarios, the computational time has a linear behaviour as $N$ increases.

## VI. Conclusion

From the above results, it can be seen that although the mathematical simulation model is providing better values of WSR for the system than the DNN, the computational time is extremely high for the mathematical model. The DNN model yields suboptimal values, but the computational time is remarkably low. Hence, in real time scenario, the usage of DNN would be more suitable.

## VII. Timeline

- Literature Review and understanding the existing work to be finished by midsem (completed).
- One week after midsem: Implement an analytical model to maximize the sum rate/SINR (completed).
- Implementation of the DNN after midsem. Hyperparameter Tuning alongside DNN modelling (completed).
- Report writing before endsem (completed).

## VIII. Future Work

In the future we plan to analyze the complexity of both the mathematical model and the DNN. The mathematical model has shown higher time complexity in terms of time taken, however we want to establish a formal time complexity in terms of $\mathcal{O}(N)$. Further we also plan to analyze the min-max optimization problem, where the optimization problem becomes maximizing the throughput of the user with the worst throughput.

## IX. Code Repository

https://github.com/GrandpaHetRocks/WCE-Project

## References


[1] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M.-S. Alouini, and R. Zhang, “Wireless communications through reconfigurable intelligent surfaces,” *IEEE Access*, vol. 7, pp. 116 753–116 773, 2019.

[2] Q. Wu and R. Zhang, “Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network,” *IEEE Communications Magazine*, vol. 58, no. 1, pp. 106–112, 2020.

[3] Q. U. A. Nadeem, A. Kammoun, A. Chaaban, M. Debbah, and M.-S. Alouini, “Intelligent reflecting surface assisted wireless communication: Modeling and channel estimation.”

[4] Y.-C. Liang, R. Long, Q. Zhang, J. Chen, H. V. Cheng, and H. Guo, “Large intelligent surface/antennas (lisa):making reflective radios smart.”

[5] X. Tan, Z. Sun, D. Koutsonikolas, and J. M. Jornet, “Enabling indoor mobile millimeter-wave networks based on smart reflect-arrays,” in *IEEE INFOCOM 2018 - IEEE Conference on Computer Communications*, 2018, pp. 270–278.

[6] F. Liu, O. Tsilipakos, A. Pitilakis, A. C. Tasolamprou, M. S. Mirmoos, N. V. Kantartzis, D.-H. Kwon, M. Kafesaki, C. M. Soukoulis, and S. A. Tretyakov, “Intelligent metasurfaces with continuously tunable local surface impedance for multiple reconfigurable functions.”

[7] L. L. et al., “Electromagnetic reprogrammable coding-metasurface holograms.”

[8] D. Mishra and H. Johansson, “Intelligent metasurfaces with continuously tunable local surface impedance for multiple reconfigurable functions.”

[9] Q. Wu and R. Zhang, “Weighted sum power maximization for intelligent reflecting surface aided swipt.”

[10] M. Cui, G. Zhang, and R. Zhang, “Secure wireless communication via intelligent reflecting surface.”

[11] J. Chen, Y.-C. Liang, Y. Pei, , and H. Guo, “Intelligent reflecting surface: A programmable wireless environment for physical layer security.”

[12] H. Shen, W. Xu, S. Gong, Z. He, , and C. Zhao, “Secrecy rate maximization for intelligent reflecting surface assisted multi-antenna communications.”

[13] X. Tan, Z. Sun, J. M. Jornet, , and D. Pados, “Increasing indoor spectrum sharing capacity using smart reflect-array.”

[14] C. Liaskos, S. Nie, A. Tsioliaridou, A. Pitsillides, S. Ioannidis, and I. Akyildiz, “A new wireless communication paradigm through software-controlled metasurfaces.”

[15] E. Björnson, L. Sanguinetti, H. Wymeersch, J. Hoydis, and T. L. Marzetta, “Massive mimo is a reality—what is next?: Five promising research directions for antenna arrays.”

[16] M. D. R. et al., “Smart radio environments empowered by reconfigurable ai meta-surfaces: An idea whose time has come.”

[17] S. V. Hum and J. Perruisseau-Carrier, “Reconfigurable reflectarrays and array lenses for dynamic antenna beam control: A review.”

[18] K. N. et al., “Reconfigurable intelligent surfaces vs. relaying: Differences, similarities, and performance comparison.”

[19] H. Q. Ngo, H. A. Suraweera, M. Matthaiou, and E. G. Larsson, “Multipair full-duplex relaying with massive arrays and linear processing.”

[20] E. Björnson, O. Özdogan, and E. G. Larsson, “Intelligent reflecting surface vs. decode-and-forward: How large surfaces are needed to beat relaying?”

[21] Q. Wu and R. Zhang, “Intelligent reflecting surface enhanced wireless network: Joint active and passive beamforming design.”

[22] ——, “Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming.”

[23] C. Huang, A. Zappone, M. Debbah, , and C. Yuen, “Achievable rate maximization by passive intelligent mirrors.”

[24] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen, “Reconfigurable intelligent surfaces for energy efficiency in wireless communication.”

[25] Y. Han, W. Tang, S. Jin, C. Wen, and X. Ma, “Large intelligent surface-assisted wireless communication exploiting statistical csi.”

[26] Q.-U.-A. Nadeem, A. Kammoun, A. Chaaban, M. Debbah, and M.-S. Alouini, “Large intelligent surface assisted mimo communications.”

[27] H. Guo, Y.-C. Liang, J. Chen, and E. G. Larsson, “Weighted sum-rate maximization for reconfigurable intelligent surface aided wireless networks,” *IEEE Transactions on Wireless Communications*, vol. 19, no. 5, pp. 3064–3076, 2020.