Non-Orthogonal Multiple Access Assisted by Reconfigurable Intelligent Surface Using Unsupervised Machine Learning

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***Abstract*—Nonorthogonal multiple access (NOMA) with multi-antenna base station (BS) is a promising technology for next-generation wireless communication, which has high potential in performance and user fairness. Since the performance of NOMA depends on the channel conditions, we can combine NOMA and reconfigurable intelligent surface (RIS), which is a large and passive antenna array and can optimize the wireless channel. However, the high dimensionality makes the RIS optimization a complicated problem. In this work, we propose a machine learning approach to solve the problem of joint optimization of precoding and RIS configuration. We apply the RIS to realize the quasi-degradation of the channel, which allows for optimal precoding in closed form. The neural network architecture RIS-net is used, which is designed dedicatedly for RIS optimization. The proposed solution is superior to the works in the literature in terms of performance and computation time.**

***Index Terms*—non-orthogonal multiple access, reconfigurable intelligent surface, machine learning, quasi-degradation.**

I. Introduction

The nonorthogonal multiple access (NOMA) is a promising solution for future multiple access technique. Unlike spatial division multiple access (SDMA), which treats interference as noise, NOMA let users apply successive interference cancellation (SIC) to decode signals from the strongest one, subtract it from the received signal, until the desired signal of the user is decoded. It has been shown that NOMA has advantages in terms of spectral and energy efficiency as well as user fairness [1].

Compared to NOMA with single-antenna base stations (BSs) [2], precoding of NOMA with multi-antenna BSs has a higher potential of performance but also confronts new challenges. It is proven that optimal precoding in a degraded multi-user multiple-input-single-output (MISO) channel achieves the performance of the optimal superposition coding (SC) and SIC [3]. The degraded channel, however, is rare in reality. Therefore, the concept of *quasi-degradation* is introduced. A closed-form solution of optimal precoding is derived for quasi-degraded channels [4], [5]. Although the quasi-degradation is a relaxation compared to degradation, this prerequisite is still a major challenge for the application. As a solution, we propose to apply the reconfigurable intelligent surface (RIS) to optimize the channel.

RIS is a large antenna array composed of many passive antennas. It receives signals from the transmitter, performs a simple signal processing without power amplification (e.g., phase shifting), and transmits them to the receiver. Due to the simple structure, low cost, and high integrability with other communication technologies, the RIS is widely considered as a key enabling technology of the next-generation wireless communication systems [6], [7]. For decades, the channels were considered given and could not be modified. The RIS enables a new opportunity to optimize the channels to become quasi-degraded [8]. Moreover, among the quasi-degraded channels, more advantageous channels (e.g., with higher channel gains) are able to realize a higher performance. These two considerations imply that the RIS can be a good company to NOMA [9]. In the literature, optimization of multi-antenna NOMA with an RIS has been performed with alternating difference-of-convex programming [10], successive convex approximation [8], accurate and approximated closed-form solution [11] as well as machine learning [12]–[15]. While the analytical methods [8], [10], [11] are constrained by the suboptimality due to approximation and complexity, the machine learning approaches [12]–[15] have poor scalability (all the works listed here assume less than 100 RIS antennas, which are far less than the vision of thousands of antennas [6]).

This work presents a joint optimization of precoding and RIS configuration with machine learning. The dedicated and scalable neural network architecture RISnet [16] is applied such that we can optimize a much larger RIS with up to 1024 antennas within a very short time because RISnet can parallelize the computation for each antenna. We will show that the proposed solution is superior than the aforementioned works in terms of performance and computation time.

II. System Model and Problem Formulation

The system model is an RIS-aided downlink scenario with multiple users. In order to achieve a compromise between complexity and performance, we assume two users in this work[1], which is a widely applied assumption in the literature [4], [5], [8]. The system model is shown in Fig. 1.

The BS has M antennas whereas the RIS is controlled by the BS and has N antennas (elements). The user equipments

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[1] An extension to more users is possible in two ways: user clustering and higher order NOMA processing.

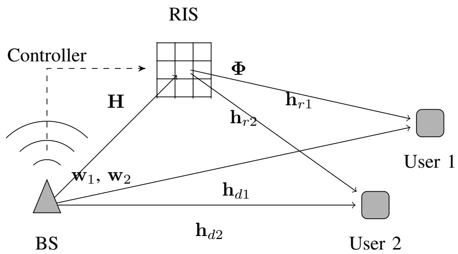

Fig. 1. System model of RIS-assisted downlink broadcast channel.

(UEs) have one antenna each, which results in a multi-user MISO channel.

The received symbol y_k of user k is calculated as

$$y_k = \mathbf{h}_k^H \left(\mathbf{w}_1 x_1 + \mathbf{w}_2 x_2\right) + n_k, \quad k = 1, 2, \tag{1}$$

where $x_k \in \mathbb{C}$ is the transmitted symbol for user k, $E\left[\|x_k\|^2\right] = 1$, $\mathbf{w}_k \in \mathbb{C}^M$ is the precoding vector for user k and $n_k \sim \mathcal{N}_{\mathbb{C}}(0, \sigma^2)$ is additive white Gaussian noise. The channel $\mathbf{h}_k \in \mathbb{C}^{M\times 1}$ is the sum of the channel via RIS and the direct channel, i.e.

$$\mathbf{h}_k^H = \mathbf{h}_{rk}^H \mathbf{\Phi} \mathbf{H} + \mathbf{h}_{dk}^H, \quad k = 1, 2, \tag{2}$$

where $\mathbf{h}_{dk}^H \in \mathbb{C}^{1\times M}$ is the direct channel from BS to user k, $\mathbf{h}_{rk}^H \in \mathbb{C}^{1\times N}$ is the channel from RIS to user k, $\mathbf{H} \in \mathbb{C}^{N\times M}$ is the channel from BS to RIS, $\mathbf{\Phi} \in \mathbb{C}^{N\times N}$ is the diagonal signal processing matrix of the RIS. The diagonal elements ϕ_{nn} in row n and column n is $\phi_{nn} = e^{j\phi_n}$, which describes the phase shifts of the nth RIS antenna.

Without loss of generality, we assume that UE 1 has the stronger channel gain and UE 2 has the weaker channel gain. Following the SIC principle, UE 1 first decodes the stronger signal for UE 2, subtracts it from the received signal and decodes the signal for UE 1 without interference, whereas UE 2 treats the signal for UE 1 as interference and decodes the signal for UE 2 directly. Signal-to-interference-noise ratio (SINR) of signal for UE 2 at UE 1 S_{21}, signal-to-noise ratio (SNR) of signal for UE 1 at UE 1 S_1 and SINR of signal for UE 2 at UE 2 S_{22} are computed as

$$S_{21} = \frac{\mathbf{h}_1^H \mathbf{w}_2 \mathbf{w}_2^H \mathbf{h}_1}{\mathbf{h}_1^H \mathbf{w}_1 \mathbf{w}_1^H \mathbf{h}_1 + \sigma^2}, \tag{3}$$

$$S_1 = \frac{\mathbf{h}_1^H \mathbf{w}_1 \mathbf{w}_1^H \mathbf{h}_1}{\sigma^2}, \tag{4}$$

$$S_{22} = \frac{\mathbf{h}_2^H \mathbf{w}_2 \mathbf{w}_2^H \mathbf{h}_2}{\mathbf{h}_2^H \mathbf{w}_1 \mathbf{w}_1^H \mathbf{h}_2 + \sigma^2}, \tag{5}$$

respectively. The achievable rates R_1 for UE 1 and R_2 for UE 2 are expressed as

$$R_1 = \log\left(1 + S_1\right), \tag{6}$$

$$R_2 = \min\left\{\log\left(1 + S_{21}\right), \log\left(1 + S_{22}\right)\right\}. \tag{7}$$

Our objective is to minimize the transmission power of the BS, which is given by $||\mathbf{w}_1|| + ||\mathbf{w}_2||$, by tuning the precoding vectors $\mathbf{w}_1$, $\mathbf{w}_2$ and the RIS configuration $\mathbf{\Phi}$, subject to the required rates r_1 of UE 1 and r_2 of UE 2. This problem can be formulated as[2] [5]

$$\begin{aligned}
\min_{\mathbf{w}_1, \mathbf{w}_2, \mathbf{\Phi}} \quad & P = \|\mathbf{w}_1\|^2 + \|\mathbf{w}_2\|^2, && \text{(8a)}\\
\text{subject to} \quad & S_1 \geq 2^{r_1} - 1, && \text{(8b)}\\
& \min\left\{S_{21}, S_{22}\right\} \geq 2^{r_2} - 1, && \text{(8c)}\\
& |\phi_{nn}| = 1, && \text{(8d)}\\
& \phi_{nn'} = 0 \text{ for } n \neq n'. && \text{(8e)}
\end{aligned}$$

III. Optimal Precoding in Quasi-Degraded Channels

Given an RIS configuration $\mathbf{\Phi}$, the optimization problem (8) with respect to $\mathbf{w}_1$ and $\mathbf{w}_2$ is not trivial to solve. However, it is proved in [4], [5] that there exists a closed-form optimal solution to $\mathbf{w}_1$ and $\mathbf{w}_2$ for quasi-degraded broadcast channels. The broadcast channel is considered quasi-degraded if

$$Q = \frac{1 + r_1}{\cos^2\psi} - \frac{r_1 \cos^2\psi}{\left(1 + r_2\left(1 - \cos^2\psi\right)\right)^2} \leq \frac{\|\mathbf{h}_1\|^2}{\|\mathbf{h}_2\|^2} \tag{9}$$

where

$$\cos\psi = \frac{\mathbf{h}_1^H \mathbf{h}_2 \mathbf{h}_2^H \mathbf{h}_1}{\|\mathbf{h}_1\| \|\mathbf{h}_2\|}. \tag{10}$$

In a quasi-degraded channel, the optimal precoding vectors are obtained by [5]

$$\mathbf{w}_1^* = \alpha_1((1 + r_2)\mathbf{e}_1 - r_2 \mathbf{e}_2^H \mathbf{e}_1 \mathbf{e}_2) \tag{11}$$

$$\mathbf{w}_2^* = \alpha_2 \mathbf{e}_2 \tag{12}$$

where

$$\mathbf{e}_1 = \frac{\mathbf{h}_1}{\|\mathbf{h}_1\|}, \tag{13}$$

$$\mathbf{e}_2 = \frac{\mathbf{h}_2}{\|\mathbf{h}_2\|}, \tag{14}$$

$$\alpha_1^2 = \frac{r_1}{\|\mathbf{h}_1\|^2} \frac{1}{(1 + r_2 \sin^2\psi)^2}, \tag{15}$$

$$\alpha_2^2 = \frac{r_2}{\|\mathbf{h}_2\|^2} + \frac{r_1}{\|\mathbf{h}_1\|^2} \frac{r_2 \cos^2\psi}{(1 + r_2 \sin^2\psi)^2}. \tag{16}$$

From the analysis above we can see that the performance of NOMA depends heavily on the channel for two reasons. 1) A prerequisite to apply the optimal precoding (11) and (12) is the quasi-degradation of the channel (9). 2) Among the quasi-degraded channels, more advantageous channels (e.g., with higher channel gains) are able to realize a lower transmission power subject to the rate requirements. These two considerations imply that the RIS can be a good company to NOMA because its ability to make a channel quasi-degraded and to optimize the quasi-degraded channel for a lower transmission power. In Section IV, we will introduce a machine learning approach that optimize the RIS configuration.

[2]By assuming no maximum transmit power, the problem is always feasible.

IV. Machine Learning Solution for Joint Precoding and RIS Configuration

A. Objective Function and Framework of Unsupervised Learning

The objective function defines how the neural network is optimized. It should 1) enforce the quasi-degradation (9) since it is the prerequisite of applying the optimal precoding (11) and (12), 2) minimize the transmission power in the quasi-degraded channel. The objective function is therefore formulated as

$$L = \log\left(1 + \text{ReLU}\left(Q - \frac{\|\mathbf{h}_1\|^2}{\|\mathbf{h}_2\|^2}\right)\right) + \epsilon P, \tag{17}$$

where the first term is the penalty if the channel is not quasi-degraded and the second term is the transmission power, the constant factor $\epsilon > 0$ is chosen to balance the effort to make all channels quasi-degraded and to minimize the transmission power.

We define the neural network as N_θ, which is a function parameterized by θ and maps from the channel feature $\mathbf{\Gamma}$, which will be defined in Section IV-B, to the RIS phase shifts $\mathbf{\Phi}$, i.e., $\mathbf{\Phi} = N_\theta(\mathbf{\Gamma})$. With the optimal precoding for quasi-degraded channels presented in Section III, our objective function L is fully determined by the channel feature $\mathbf{\Gamma}$, and the RIS configuration $\mathbf{\Phi}$. We can write the objective as $L(\mathbf{\Gamma}, \mathbf{\Phi}) = L(\mathbf{\Gamma}, N_\theta(\mathbf{\Gamma}); \theta)$. Note that the right hand side of the equation emphasizes that L depends on the parameter θ given $\mathbf{\Gamma}$.

We collect massive channel data in a training data set $\mathcal{D}$ and formulate the unsupervised machine learning problem as

$$\min_\theta \sum_{\mathbf{\Gamma} \in \mathcal{D}} L(\mathbf{\Gamma}, N_\theta(\mathbf{\Gamma}); \theta). \tag{18}$$

In this way, we optimize the function which maps from any $\mathbf{\Gamma} \in \mathcal{D}$ to $\mathbf{\Phi}$. This optimization process is called *training*. If the data set is general enough, we would expect that a channel feature $\mathbf{\Gamma}' \notin \mathcal{D}$, which, however, is independent and identically distributed (i.i.d.) as channel features in $\mathcal{D}$, can also be mapped to a good RIS configuration. The performance evaluation of $L(\mathbf{\Gamma}', N_\theta(\mathbf{\Gamma}'))$ for $\mathbf{\Gamma}' \notin \mathcal{D}$ and a trained and fixed N_θ is called *testing*.

B. Channel Features

We assume that $\mathbf{H}$ is constant because both BS and RIS are fixed. The neural network requires both $\mathbf{h}_{dk}$ and $\mathbf{h}_{rk}, k = 1, 2$ to compute $\mathbf{\Phi}$. The RIS optimization problem is complicated mainly because of the large number of RIS antennas. However, the way that one single RIS antenna contributes to the overall channel is the same, i.e., the RIS antennas are homogeneous. Motivated by this fact, we apply the same information processing for every RIS antenna in one layer of the multi-layer deep neural network. This requires that the input of the deep neural network, i.e., the channel feature, should be a stack of channel features per RIS antenna. While this is straightforward for $\mathbf{h}_{rk}^H$ because column n of $\mathbf{h}_{rk}^H$ is the channel gain from RIS antenna n to user k, it is difficult for $\mathbf{h}_{dk}^H$ since $\mathbf{h}_{dk}^H$ is the direct channel from RIS to user k. Therefore, we apply the following trick:

$$\mathbf{h}_k^H = \mathbf{h}_{rk}^H \mathbf{\Phi} \mathbf{H} + \mathbf{h}_{dk}^H = (\mathbf{h}_{rk}^H \mathbf{\Phi} + \mathbf{j}_k^H)\mathbf{H}, \tag{19}$$

where we define $\mathbf{j}_k^H = \mathbf{h}_{dk}^H \mathbf{H}^+$ with $\mathbf{H}^+$ being the pseudo-inverse of $\mathbf{H}$. Column n of vector $\mathbf{j}_k^H \in \mathbb{C}^{1 \times N}$ can then be mapped to RIS antenna n unambiguously. The channel feature $\mathbf{\Gamma}$ is defined as

$$\begin{aligned} \mathbf{\Gamma} = (&|\mathbf{h}_{r1}^H|; \arg(\mathbf{h}_{r1}^H); |\mathbf{j}_1^H|; \arg(\mathbf{j}_1^H) \\ &|\mathbf{h}_{r2}^H|; \arg(\mathbf{h}_{r2}^H); |\mathbf{j}_2^H|; \arg(\mathbf{j}_2^H)), \end{aligned} \tag{20}$$

where the semicolon indicates a new row of the matrix. $\mathbf{\Gamma}$ has a shape of $8 \times N$. Column n of $\mathbf{\Gamma}$ is the channel feature of RIS antenna n.

C. The RISnet Architecture

In this section, we present the RISnet architecture, which is first introduced in [16]. The basic idea of the RISnet is that an RIS antenna needs its local information as well as the information of the whole RIS to make a good decision on its configuration. The local information of an antenna is obtained based on the information of the considered antenna only (therefore it is called local information). The global information is the mean of the information of all RIS antennas, which is the same to all RIS antennas and represents the information of the whole antenna array (therefore it is called global information).

Denote the input of layer i as $\mathbf{F}_i$ of shape $B_i \times N$, where B_i is the feature dimension of layer i and the nth column of $\mathbf{F}_i$ is the feature vector of RIS antenna n. For $i = 1$, $\mathbf{F}_1^u$ (i.e., the input of the RISnet) is defined as the channel feature

$$\mathbf{F}_1 = \mathbf{\Gamma}. \tag{21}$$

For layer $i < L$, we compute the local feature as

$$\mathbf{F}_{i+1}^l = \text{ReLU}(\mathbf{M}_i^l \mathbf{F}_i + \mathbf{b}_i^l) \tag{22}$$

where $\mathbf{M}_i^l$ of shape $B_{i+1}^l \times B_i$ and $\mathbf{b}_i^l$ of shape $B_{i+1}^l \times 1$ are trainable weight and bias for local feature in layer i, where B_{i+1}^l is the local feature dimension for layer $i+1$, and ReLU is the rectified linear unit function. Note that $\mathbf{b}_i^l$ is added to every column to $\mathbf{M}_i^l \mathbf{F}_i$. The global feature is computed as

$$\mathbf{F}_{i+1}^g = \text{ReLU}(\mathbf{M}_i^g \mathbf{F}_i + \mathbf{b}_i^g) \times \mathbf{1}_N / N \tag{23}$$

for all RIS antennas, where $\mathbf{M}_i^g$ of shape $B_{i+1}^g \times B_i$ and b_i^g of shape $B_{i+1}^g \times 1$ are trainable weight and bias for global feature in layer i, with B_{i+1}^g being the global feature dimension of layer $i+1$, and $\mathbf{1}_N$ is a matrix of all ones of shape $N \times N$.

The output feature by layer i is the concatenation of the channel features and the two features defined above:

$$\mathbf{F}_{i+1}^u = \left((\mathbf{\Gamma})^T, \left(\mathbf{F}_{i+1}^l\right)^T, \left(\mathbf{F}_{i+1}^g\right)^T\right)^T. \tag{24}$$

Therefore, the feature dimension of the layer $i+1$ is $B_{i+1} = 8 + B_{i+1}^l + B_{i+1}^g$ since the channel feature dimension is 8.

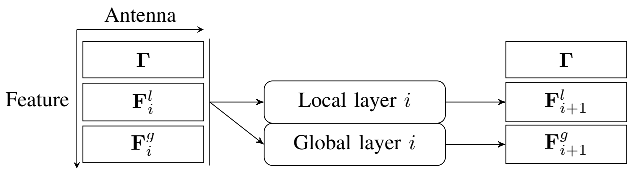

Fig. 2. Information processing of one layer in the RISnet.

In the final layer ($i = L$), the output of the RISnet is computed as

$$\mathbf{f}_{L+1} = \mathrm{ReLU}\left(\mathbf{m}_L \sum_u \mathbf{F}_L^u + b_L\right) \tag{25}$$

where $\mathbf{m}_L$ and b_L are trainable weights and bias, respectively. The RIS signal processing matrix $\mathbf{\Phi}$ is obtained by

$$\mathbf{\Phi} = \mathrm{diag}(e^{j\mathbf{f}_{L+1}}). \tag{26}$$

Since elements in $\mathbf{f}_{L+1}$ are always real, we make sure the amplitudes of the diagonal elements in $\mathbf{\Phi}$ are 1 and the off-diagonal elements in $\mathbf{\Phi}$ are 0.

The information processing of one layer of the permutation-invariant RISnet is illustrated in Fig. 2. The RISnet has 8 layers and 8201 trainable parameters in total. Compared to it, a single layer of 8192 inputs and outputs (1024 antennas and 8 feature per antenna) has 67117056 parameters. Training of the neural work is performed as Algorithm 1 describes.

Algorithm 1 RISnet training

Randomly initialize RISnet.
repeat
  Randomly select a batch of data samples.
  Compute $\mathbf{\Phi} = N_\theta(\mathbf{\Gamma})$ for every data sample in the batch.
  Compute the channel $\mathbf{h}_k$ for $k = 1, 2$ and every data sample in the batch.
  Compute the objective function (17) for every data sample in the batch.
  Compute the gradient of the objective w.r.t. the neural network parameters
  Perform a stochastic gradient ascent step with the Adam optimizer
until Predefined number of iterations achieved

D. Complexity Analysis

Due to the separation between offline training and online testing the online performance of the machine learning approach only depends on the size of the neural network. Obtaining the output of the trained RISnet requires only the computation of a forward propagation of the trained neural network [17]. For this reason, the online complexity of the proposed machine learning based method is much lower than the complexity of the SDR-based approaches from [10] which instead requires solving convex problems in each iteration.

TABLE I
SETTING AND PARAMETER VALUES

Parameter	Value
Number of BS antennas	9
Number of RIS antennas	{64, 256, 1024}
Number of layers	8
Learning rate	5×10^{-6}
Feature dimension	8
Iterations	25000
Batch size	512
Number of data samples in training set	10240
Number of data samples in testing set	1024

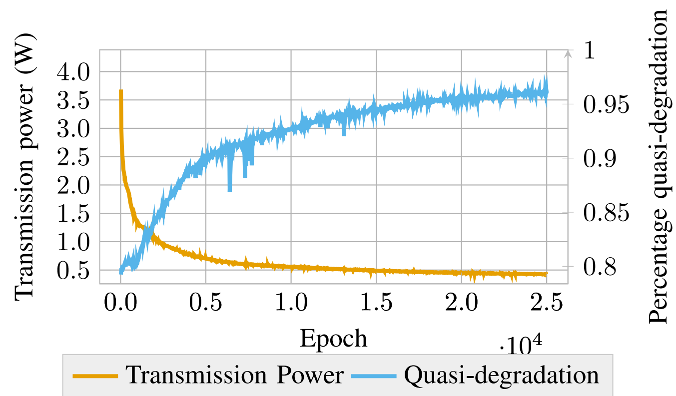

Fig. 3. Training of the RISnet with $N = 1024$.

V. TRAINING AND TESTING RESULTS

We apply the DeepMIMO framework to generate channel data [18]. We used the Outdoor 1 scenario with an intersection and placed the BS, the RIS and the users so that there is a line of sight between the BS and the RIS as well as between the RIS and the users, but not between the BS and the users. Important parameters of scenario and model are presented in Table I. The learning curve is shown in Fig. 3. The effect of the parameter ϵ is presented in Table II. To estimate the performance the transmission power is compared to the best result of 1000 randomly generated phase shifts also using the optimal precoding for quasi-degraded channels. This simple baseline was used owing to the scalability up to 1024 RIS-elements. For 64 RIS-elements we also used an alternating SDR-based algorithm as described in [10]. For larger numbers of RIS-elements this approach was not usable due to high memory consumption. The results are presented in Fig. 4. We can observe that the proposed method outperforms the baseline for all numbers of RIS antennas.

VI. CONCLUSION

We consider the joint optimization of NOMA precoding and RIS optimization. The precoding guarantees the optimal performance under the quasi-degraded channel constraint and the RIS optimizes the channel to be quasi-degraded and to minimize the transmission power subject to the rate constraints. The neural network architecture RISnet is applied

TABLE II
TRAINING AND TEST RESULTS FOR DIFFERENT VALUES OF ϵ WITH $N = 1024$.

	$\epsilon = 1$		$\epsilon = 0.1$		$\epsilon = 0.01$	
	Power	QD percentage	Power	QD percentage	Power	QD percentage
Training	0.325	91.6 %	0.421	96.1 %	2.353	96.7 %
Test	0.505	92.0 %	0.431	93.4 %	2.402	94.7 %

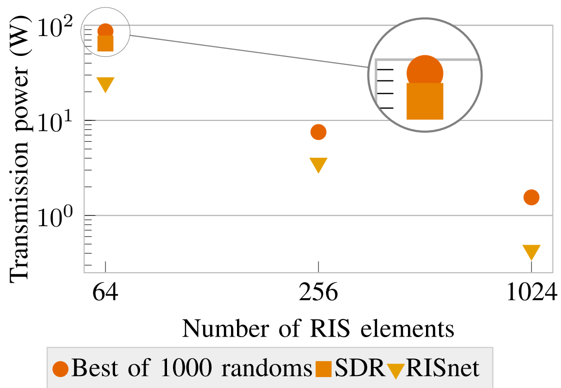

Fig. 4. Testing results of different approaches (SDR only works with 64 RIS elements).

to configure the RIS, which is designed dedicatedly for RIS optimization and its number of parameters is independent from the number of RIS-elements, which makes it scalable. We assume up to 1024 RIS-elements, which are far more than in the assumptions in most literatures. Testing results show good performance compared to the baseline and instant computation time. Source code and data set are available under https://github.com/bilepeng/risnet_noma.

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