

Evaluation of Autoencoder-based Communications with Reconfigurable Intelligent Surfaces

Thi-Nga Dao¹, Chi-Hieu Ta²

^{1,2}Le Quy Don Technical University, Ha Noi, Vietnam

Correspondence: Thi-Nga Dao (daothinga@mta.edu.vn)

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Abstract: Reconfigurable intelligent surfaces (RIS) have emerged as a promising technique for wireless communication in 5G and beyond. In an environment with lots of physical obstacles, RIS provides an alternative solution to the coverage problem by beam-forming signal towards the desired direction of the receiver. Due to the fixed constellation diagram, traditional modulation schemes cannot be used for the RIS-aided communication system with the receiver movement. In this work, we aim to design and evaluate an autoencoder-based communication model with RIS support, which can adapt to changes in the environment and the receiver's position. Specifically, we use neural networks to present the encoder and decoder of the system and the parameters of these networks are trained to minimize the reconstruction error at the receiver. The simulation setup is based on characteristics of the environment and real RIS. Performance results show the benefits of RIS when a physical obstruction is present between the transmitter and receiver. Moreover, we prove that the selection of RIS codeword plays an important role in system performance.

Keywords: *autoencoder-based communications, reconfigurable intelligent surfaces*

I. INTRODUCTION

Reconfigurable intelligent surfaces (RIS) consisting of hundreds to thousands of passive reflecting units have drawn great attention from both academia and industry [1–3]. RIS can be applied to various applications such as wireless communication, wireless power transfer, and wireless security. By intelligently selecting the phase shift of each cell unit, RIS is capable of beam-forming to a desired direction. Thus, the RIS-aided communication system is a potential solution for the coverage problem due to the lack of a light-of-sight path between the transmitter and receiver. In this work, we model and analyze the RIS-based communication system especially when the receiver's location changes over time.

The traditional wireless communication system includes a transmitter, receiver, and a wireless channel between devices. In the transmitter, the symbol is modulated by changing a specific characteristic of the carrier signal such as amplitude, frequency, or phase. While transmitting via a wireless channel, noise with Gaussian distribution is usually added to the signal. Then, the demodulation process is executed at the receiver to determine the information sent by the sender. In the conventional communication model, the modulation block is usually fixed and the constellation diagram is pre-determined. However, a fixed constellation diagram in conventional modulation schemes such as PSK and QAM is not suitable for the case of varying receiver locations. Once the receiver moves to the new position, RIS codeword should be updated for beam-forming toward the new direction and the phase shift of the encoded signal varies accordingly. Therefore, the modulation block should generate complex signals differently so that the constellation diagram of the received signal at the receiver shows maximum separation between adjacent points. To achieve maximum performance at the receiver, we design a RIS-based communication model that adaptively modulates the information based on the receiver's location and the channel state information.

We propose and evaluate an autoencoder-based RIS-aided communication system that consists of five main blocks: transmitter, Tx-RIS channel, RIS, RIS-Rx channel, and receiver. The transmitter is in charge of signal modulation by mapping the information into complex signals with I/Q parts. To speed up training convergence, a normalization layer is added at the end of the transmitter block. While transmitting the signal via the Tx-RIS channel, the modulated signal is attenuated based on channel features including distance from Tx-RIS, antenna gain, and frequency. The amplitude and phase of the modulated signal can be adjusted by controlling the PIN diode attached to each cell

unit. A PIN diode is used as a load of microstrip antenna where the signal is reflected. After being reflected at RIS, the signal goes through the Rx-RIS channel before arriving at the receiver. For training convergence acceleration, another normalization layer is inserted at the beginning of the receiver and the received signal is normalized in the range $[-1, 1]$. We assume that noise with Gaussian distribution is added to the received signal at the receiver. Then, the actual information is extracted from the received signal using a decoder.

As stated earlier, a flexible modulation scheme that can adapt to the receiver's location, as well as channel state information, is used. To do that, an autoencoder is used to compress the information to a complex signal at the encoder and then the decoder attempts to reconstruct the generated symbol from the compressed vector. Network parameters of AE can be trained to minimize the reconstruction difference between the generated and predicted symbols.

The main contribution of our study is listed below.

- We present the RIS-aided AE-based communication system to overcome the critical coverage problem with the change of receiver's location.
- A more practical RIS-aided communication model is introduced with pre-determined codeword selection based on the location of the receiver and with discrete phase shift by RIS.
- The communication system is evaluated using characteristics of a real RIS prototype and the real environment with different numbers of information bits and ratio of noise power to energy per bit.
- Simulation results show the feasibility of the proposed model and the huge effect of codeword selection on the performance of the communication system.

The rest of the paper is organized as follows: Section II presents basic knowledge of autoencoder and RIS. Then, the communication model is described in Section III. Section IV presents the network setup and analyzes the performance of the proposed model with various network parameters. Finally, we draw the conclusion for our work in Section V.

II. RELATED STUDY

In this section, we summarize autoencoder architectures and RIS technique. Then, we compare our work with existing autoencoder-based RIS-supported communication systems to highlight advantages of the proposed model.

Autoencoders are neural networks capable of learning efficient representation of data by minimizing the construction error between the input and reconstructed data. Autoencoders can be leveraged for dimensionality reduction.

An autoencoder always consists of two parts: an encoder that maps inputs into the coding vectors with a much smaller size and a decoder for data recovery. In wireless communication systems, data is usually modulated into a radio signal that is then sent in the atmosphere environment. Existing studies [4] show that autoencoders are greatly suitable for data modulation in wireless communications. The coding vectors have two dimensions for I and Q parts. A noise layer with Gaussian distribution is usually added to reflect the natural features of environments. The number of input units and output units is the number of possible symbols.

RIS has recently emerged as a promising technique for coverage and data-rate improvement for wireless communication systems in mmWave bands, which are badly affected by physical obstructions as shown in Figure 2. Wireless power transfer systems become more efficient with the support of RIS, which is proven in a lot of research [5–7]. Moreover, RIS can be leveraged to enhance the security of wireless communication systems by not allowing signal transmission toward eavesdroppers. RIS consisting of a programmable antenna array can be used to beamform the RF signal toward the receiver's direction. Existing works analyzed the performance of these surfaces using both simulations and real devices.

We first present the system model of RIS-aided communication. Assume that the LoS link is blocked by physical obstacles, the received signal at the receiver can be written as:

$$y = h_{TR}^T \Psi h_{RR} x + n \quad (1)$$

where $h_{TR} \in \mathbb{R}^{N \times 1}$ denotes the channel response between transmitter and RIS and $h_{RR} \in \mathbb{R}^{N \times 1}$ is for the channel response between RIS and receiver. Meanwhile, $\Psi \in \mathbb{R}^{N \times N}$ is a diagonal matrix of RIS interaction. We define $\psi = \text{diag}(\Psi)$ as the RIS beamforming vector and the optimal value is determined as:

$$\psi^* = \text{argmax}(a_{TR} \cdot a_{RR} \psi) \quad (2)$$

where a_{TR} and a_{RR} are the phase shift of TX-RIS and RIS-RX channels, respectively. The optimal RIS phase-shifting configuration is derived as:

$$\psi^* = -(a_{TR} + a_{RR}) \quad (3)$$

Because of hardware limitations, there is a huge challenge for the implementation of RIS with continuous phase shift values. In practice, RIS with a limited set of reflection angles becomes popular. For example, authors in [8] evaluated the response of a real-world 160-cell RIS and experimental results show that RIS created a delay of 0° or 180° while beamforming the signal to the receiver's position.

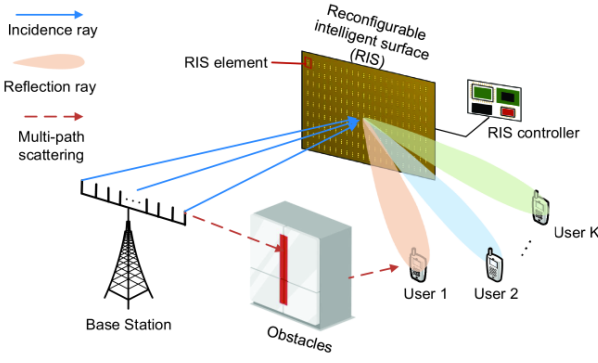


Figure 1: Wireless communications for multi-users with support of RIS [9]

There are some existing works on evaluating the autoencoder-based communication system with RIS support [10, 11]. In [10], they assume that there is a physical obstruction that accounts for a loss between transmitter and receiver. Simulation results show that the symbol error rate of the AE-based RIS-aided system is better than the QPSK-modulated system. In their system, parameters are trained for codeword selection and signal modulation. However, the appropriate codeword of RIS elements should be selected first if the receiver's position is known. Since RIS acts as a directional antenna, reflecting power at the main lobe is much higher than in other directions. Therefore, in our design, we assume that the codeword is determined based on the receiver's position to simplify the system design and training. In [11], the multi-input multi-output RIS-supported AE-based system is considered with a practical channel state information. However, phase shift of RIS is a continuous value, which is not practical in RIS implementation. In our work, RIS with a limited list of codewords is considered based on real experiments in [8].

III. RIS-AIDED AUTOENCODER-BASED COMMUNICATIONS MODEL

When there is no direct path between the transmitter and receiver, RIS can be used to construct an alternative communication channel. The transmitter sends a modulated signal towards RIS and the signal is passively reflected towards the receiver's direction. The RIS controller plays an important role to tune the reflection angle of the signal, which can take values in a discrete set. Assume that RIS consists of N elements and each element is connected to a programming controller that can adjust the element's impedance and the reflected signal direction. In this work, we consider a communication system with a transmitter and a receiver.

There are five main blocks in the AE-based RIS-supported communication system: transmitter, Tx-RIS channel, RIS, RIS-Rx channel, and receiver. We describe these five blocks followed by the training procedure in detail below.

1. Transmitter architecture

A symbol s containing k information bits is fed into the transmitter to generate an I/Q sample. First, one-hot encoding is used to convert s to a vector with the size of 2^k . For example, if $k = 2$, the one-hot vectors are 1000, 0100, 0010, and 0001. Then, a fully-connected neural network (NN) is applied to map the one-hot vector to complex numbers with real and imaginary parts. The NN architecture contains a hidden layer and an output layer with tanh activation. This process can be thought of as a modulation scheme in which the amplitude and phase of I/Q sample are changed based on the input symbol. Using the autoencoder technique, the constellation diagram is learnt automatically. For example, $k = 2$ is equivalent to 4-QAM in the conventional modulation technique.

To limit the maximum transmission power, a normalization layer is used after the NN model:

$$x = \frac{x}{\sqrt{\max(\|x\|_2^2)}} \quad (4)$$

There are no trainable parameters in the normalization layer. For the average power constraint, the normalization layer is implemented as:

$$x = \frac{x}{\sqrt{\text{mean}(\|x\|_2^2)}} \quad (5)$$

Max or mean operation is computed over mini-batch with batch size of 4.

2. Tx-RIS channel

This channel applies amplitude loss and phase shift to the transmitted signal x . Channel coefficient h_{TR} contains N parameters, which are in the range $[-1, 1]$. If no amplitude loss and phase shift are applied, channel coefficients are set to 1. For ease of implementation, a linear dense layer is used to simulate the Tx-RIS channel. Only amplitude loss is considered by scaling down both real and imaginary parts with the same factor. For example, if the transmitted signal $x = [0.6, 0.8]$ and the element $h_{TR} = 0.5$, the signal received at RIS will be $x_{RIS} = [0.3, 0.4]$. Path loss of Tx-RIS channel α_{TR} is derived according to free-space path loss as below.

$$\alpha_{TR} = \frac{c}{4\pi d_{TR} f} \sqrt{G_{tx} G_{RIS}} \quad (6)$$

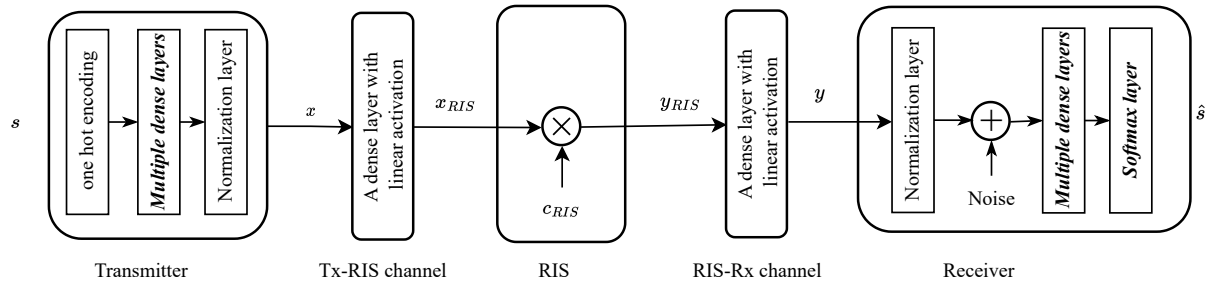


Figure 2: Autoencoder-based communications with RIS (blocks with italic and bold texts contain trainable parameters)

TABLE I: Notations used in the paper

Name	Description	Shape (if applied)
N	Number of passive elements in RIS	
s	Symbol	k
k	The number of information bits	
x	I/Q samples generated by transmitter	2
h_{TR}	Channel between transmitter and RIS	$(N, 1)$
x_{RIS}	Signal received at RIS	$2N$
c_{RIS}	Codeword of RIS	$2N$
y_{RIS}	Signal output at RIS	$2N$
y	Signal received at receiver	2
h_{RR}	Channel between RIS and receiver	$(N, 1)$
$\hat{s}$	Constructed signal at the receiver	k
β	Standard deviation of noise	
R	Communication rate	
E_b	Energy per bit	
N_0	Power spectrum density	
α_{TR}	Path loss of Tx-RIS channel	
α_{RR}	Path loss of RIS-Rx channel	
c	Transmission speed	
d_{TR}	The distance between transmitter and RIS	
d_{RR}	The distance between RIS and receiver	
G_{Tx}	Gain of transmitter antenna	
G_{RIS}	Gain of RIS antenna	
G_{Rx}	Gain of receiver antenna	

where c is the transmission speed of the radio signal in the atmosphere, d_{TR} is the distance between transmitter and RIS, f denotes signal frequency while G_{Tx} and G_{RIS} represent antenna gains of transmitter and RIS. Channel coefficient is randomly selected in range $\alpha_{TR} \times [h_{low}, h_{high}]$.

Generally, two parts of x_{RIS} are computed as follows:

$$x_{RIS}[0 : N] = x[0] \times h_{TR} \quad (7)$$

$$x_{RIS}[N : 2N] = x[1] \times h_{TR}. \quad (8)$$

Then, we combine these $x_{RIS}[0 : N]$ and $x_{RIS}[N : 2N]$ into x_{RIS} . In our work, parameters in the Tx-RIS channel are constant and could not be updated during training.

3. RIS architecture

In our system, RIS operates as a reflectarray antenna with a reflection angle θ_d , which is determined based on position of the receiver. Codeword c_{RIS} is referred to a practical experiment in [8]. Codeword consists of N rows and two columns. Each row accounts for coefficient of each unit cell. For example, phase shift is quantized using 1 bit and amplitude of signal reflected by RIS is reduced by half. If phase shift is 0° of a specific cell unit, coefficient will be $[0.5, 0.5]$. Otherwise, for 180° phase shift, coefficient will be $[-0.5, -0.5]$. The codeword vector c_{RIS} is multiplied element-wise by x_{RIS} as below.

$$y_{RIS} = x_{RIS} \odot c_{RIS} \quad (9)$$

4. RIS-Rx channel

Similar to Tx-RIS channel, channel coefficient h_{RR} with N non-trainable parameters represents amplitude attenuation. Path loss of Tx-RIS channel α_{RR} is computed as below.

$$\alpha_{RR} = \frac{c}{4\pi d_{RR} f} \sqrt{G_{rx} G_{RIS}} \quad (10)$$

where c is the transmission speed of the radio signal in the atmosphere, d_{RR} is the distance between RIS and receiver, f denotes signal frequency while G_{rx} and G_{RIS} represent antenna gains of receiver and RIS. We define $y \in \mathbb{R}^2$ as the received signal at the receiver. The components y_I and y_Q account for the I and Q parts and are derived as follows.

$$y_I = y_{RIS}[0 : N] \times h_{RR,I} \quad (11)$$

$$y_Q = y_{RIS}[N : 2N] \times h_{RR,Q} \quad (12)$$

In this work, we do not consider phase shift and set $h_{RR,I} = h_{RR,Q} = h_{RR}$. If phase shift is taken into account, $h_{RR,I} \neq h_{RR,Q}$.

5. Receiver

The signal y has I and Q components at the receiver. The receiver architecture consists of a normalization layer followed by a noise layer, multiple dense layers, and a softmax layer. The normalization layer ensures that the received signal y has an average amplitude of 1. By doing that, the learning speed is expected to be faster since features of dense layers are in the range $[-1, 1]$ at the input of the receiver block. There is no trainable parameter in the normalization layer. Added noise with two dimensions follows Gaussian distribution with the mean of 0 and standard deviation β is:

$$\beta = \sqrt{\frac{1}{2RE_b/N_0}} \quad (13)$$

where communication rate $R = k/n$ with channel use $n = 2$ while E_0 is energy per bit and N_0 denotes noise power spectral density [4]. The noise layer varies for each sample in training and testing sets. The softmax layer includes 2^k units that represent the probability of sending 2^k symbols. The receiver will return the most likely symbol with the highest probability.

6. Training procedure

Layers with trainable parameters are denoted by italic and bold texts in Figure 2. Parameters at encoder and

TABLE II: Parameters Setup

Parameters	Description
k	$\{1, 2, 3, 4, 5, 6\}$
$\frac{E_b}{N_0}$	$\{2, 4, 6, 8, 10\}$
N	160
n	2
α_{TR}, α_{RR}	0.065
h_{low}	$[0.2, 0.8]$
h_{high}	1
Operating frequency f	5.8 GHz
Antenna gain G	10 dBi
Amplitude loss at a RIS unit	3 dB
#Training epochs	50
Learning rate	0.001

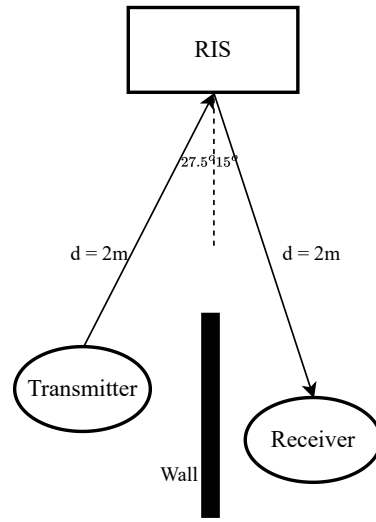


Figure 3: Network topology for performance evaluation

decoder are learnt by minimizing the cross-entropy loss function:

$$L_1 = -\frac{1}{M} \sum_{i=1}^M \sum_{j=1}^{2^k} f(s_j) \log p(\hat{s}_j) \quad (14)$$

where M is the mini-batch size, $f(s_j)$ is the one-hot vector of symbol j , $p(\hat{s}_j)$ is the probability of the constructed symbol j . L_1 achieves the minimum value when $s_j = \hat{s}_j$ for all j values.

We define θ as trainable parameters at a specific phase. After a training epoch, if using gradient descent, network parameters are updated as:

$$\theta = \theta - \eta \frac{\partial L}{\partial \theta} \quad (15)$$

where η is learning rate and L_1 is a loss function at the considered phase.

IV. PERFORMANCE EVALUATION

In this section, we first examine the RIS-aided communication system with a transmitter, a receiver, and RIS as shown in Figure 3. Assume that there is a physical obstacle between the transmitter and receiver, which makes direct transmission impossible. The distance between the transmitter/receiver and RIS is set to 2m. The incident angle is set to 27.5° and the reflection angle is set to 15° . We refer to RIS characteristics in which the PIN diode is used to control the phase shift of each unit cell in RIS. RIS comprises 160 unit cells (16×10) [8]. A nearly 180° phase shift between ON and OFF states is achieved at frequency band 5.8 GHz. Assume that the reflection amplitude is attenuated around 3 dB in both states. With the above features, we refer to the quantized phase distribution of RIS with the reflection angle of 15° in Figure 13 of [8]. Various parameters consist of the number of information bits (k), and the ratio of bit energy to noise spectral power ($\frac{E_b}{N_0}$). The antenna gain of the transmitter, receiver, and RIS is set to the same value G of 10 dBi. Then, channel amplitude loss is computed as 0.021. Since the channel is usually random, h_{TR} and h_{RR} follow uniform distribution in range $0.021 \times [h_{low}, h_{high}]$. The default value for h_{low} is 0.2. Table II summarizes the main parameters used in the experiments. A supervised learning method is used to update the network parameters of the proposed system. The number of training and test samples is set to 10^6 . When increasing k , we should use more samples for training to better distinguish between constellation points. We use accuracy at the receiver as the performance metric to evaluate the system. Accuracy is defined as the percentage of correct symbols at the receiver. In the encoder block, the transmitter has two fully-connected layers with 64 and 2 tanh units. In the decoder block, there are two fully-connected layers with 64 ReLU hidden neurons and 2^k softmax neurons at the receiver. The number of floating-point operations (FLOPs) including multiplication, addition, and division can be used to show the model complexity of the proposed system. For the setup mentioned above, the number of FLOPs in the transmitter block is: $2 \times 2^k \times 64 + 2 \times 64 \times 2 = 128 \times 2^k + 256$. The number of FLOPs of two-channel blocks is $2 \times 2 \times N = 640$. The RIS block contains $2N = 320$ operations while the number of FLOPs at the receiver is $2 \times 2 \times 64 + 2 \times 64 \times 2^k = 256 + 128 \times 2^k$. Then, the proposed system includes $1,472 + 256 \times 2^k$ operations. The learning rate is set to 0.001. The tanh activation function is used to limit the output layer in the range $[-1, 1]$, which is suitable for power constraint at the transmitter. We provide the full code to help the audience reproduce the results of this paper at <https://github.com/daothinga/AE-based-RIS-aided-communication-system>.

1. Performance results of RIS-aided communication system

First, we show the constellation generated by autoencoder with I and Q signals in Table 6 during the first training phase when $k = 3$ and $\frac{E_b}{N_0} = 6$ dB. Before training (round 0), the constellation diagram looks random. However, encoded samples are distributed far from each other over training rounds. Finally, in round 4, signals are modulated similarly to 8-PSK in which encoded samples are distributed equally on the circle with radius 1.

When phase shift is continuous, c_{RIS} can take any value in the range $[-1, 1]$. However, phase shift generated by a cell unit is usually discrete in practice. Specifically, c_{RIS} of a cell unit is set to $[0.5, 0.5]$, which corresponds to 0 phase shift and 3 dB amplitude loss, and $[-0.5, -0.5]$ for 180° phase shift and 3 dB amplitude attenuation.

Figure 5 illustrates the performance of the communication system with k varies from 2 to 6 while $\frac{E_b}{N_0}$ changes from -2 to 10. When $k = 2$, the accuracy at the receiver achieves 100% with all considered values of $\frac{E_b}{N_0}$. When increasing the number of information bits to be sent, the symbol error at the receiver becomes higher. For example, $\frac{E_b}{N_0} = 0$, accuracy at receiver drops 66.3% as k changes from 2 to 6. Undoubtedly, increasing $\frac{E_b}{N_0}$ results in better performance at the receiver.

2. Effects of codeword selection

Assume that a wrong codeword is accidentally fed to the RIS controller. As a result, received power is attenuated significantly. We assume that the receiver moves to a different location and the updated reflection angle is 45° . However, the previous codeword is still used at RIS, which presents the wrong codeword case. According to [8], the received signal is attenuated 15 dB at the receiver. We compare accuracy in two cases: correct and wrong codeword in Table III. We set k to 2 and 3 while $\frac{E_b}{N_0}$ varies from -2 dB to 10 dB with the step of 2. When using the correct codeword, we can achieve the maximum received signal power. Therefore, accuracy with the correct codeword is much higher than in the case of the wrong codeword. We can infer from Table III that codeword selection plays an important role in the receiver performance. Since the power of the main reflecting lobe is usually much greater than that of other directions, the wrong codeword causes a very low performance at the receiver.

3. Impact of channel state information

We have validated the system performance with different channel responses h_{TR} and h_{RR} . We set h_{low} to 0.2 and

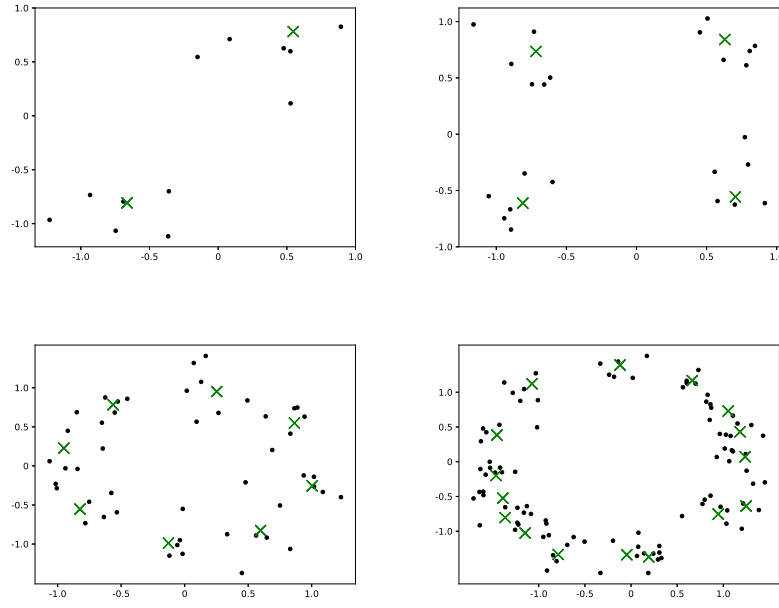
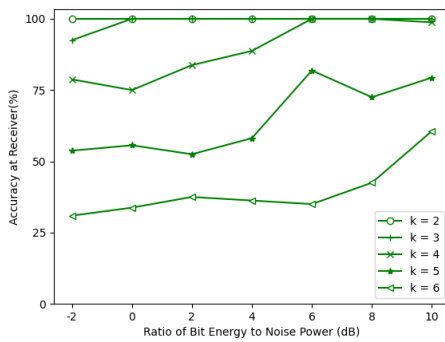
Figure 4: Encoded signals (blue) and received signals (black) with noise when $k = 1, 2, 3, 4$

TABLE III: Effects of codeword selection on Accuracy Performance

$(k, \frac{E_b}{N_0})$	Accuracy w/ correct codeword	Accuracy w/ wrong codeword
(2, -2)	100%	40%
(2, 0)	100%	60%
(2, 2)	100%	40%
(2, 4)	100%	60%
(2, 6)	100%	65%
(2, 8)	100%	55%
(2, 10)	100%	70%
(3, -2)	92.5%	35%
(3, 0)	100%	25%
(3, 2)	100%	37.5%
(3, 4)	100%	25%
(3, 6)	100%	25%
(3, 8)	100%	32.5%
(3, 10)	100%	60%

Figure 5: Performance evaluation with different values of k and $\frac{E_b}{N_0}$

0.8 while h_{high} is 1. From the results in Fig 7, we can infer that the AE-based RIS-supported communication system is able to adapt to the change in the channel environment. The performance results in the two cases are quite similar. The proposed system can generate different constellation diagrams based on channel and RIS response characteristics. The modulation scheme based on AE becomes flexible compared to the traditional modulation schemes.

4. Performance comparison between AE-based and M-PSK modulation schemes

In this subsection, we first compare the performance between AE-based and M-PSK modulation schemes with

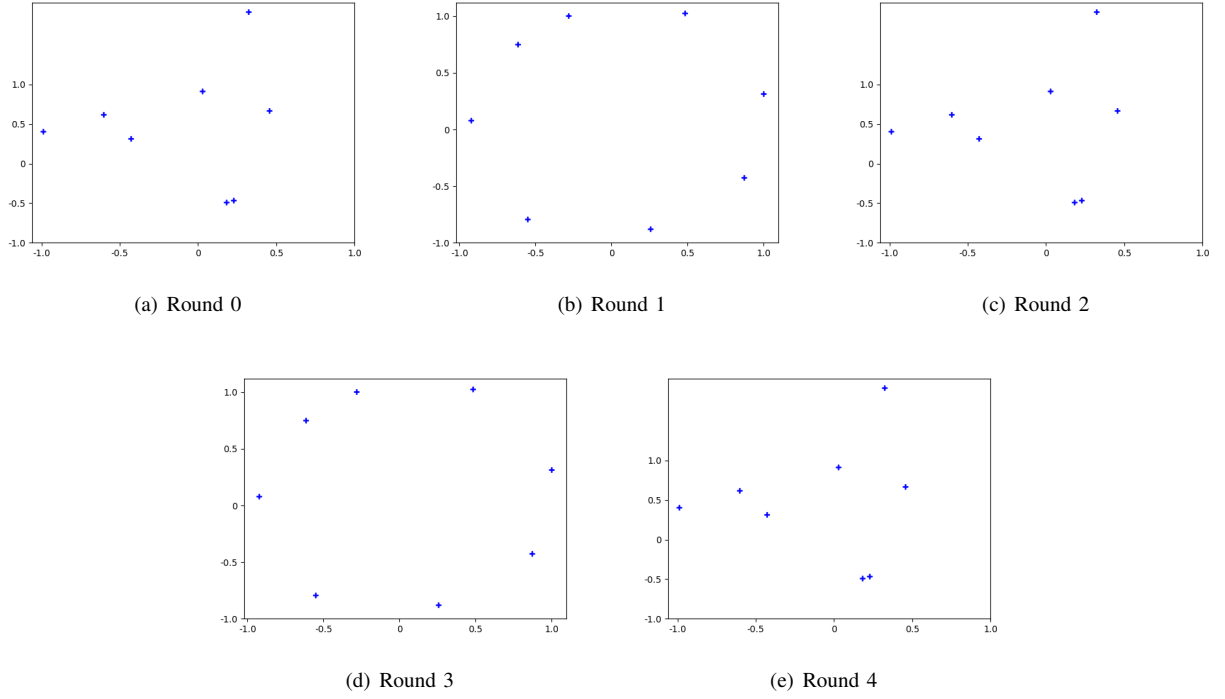
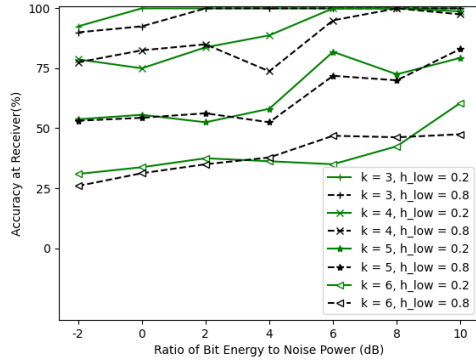

 Figure 6: Encoded signals during training with $k = 3$ and $\frac{E_b}{N_0} = 6$ dB


Figure 7: Impacts of channel response on performance of receiver

regard to block error rate (BLER) over the Gaussian channel. The experimental scenario is shown in Figure 3. We use the same network parameters as shown in Table II. For example, there are 160 RIS cells and two states (ON and OFF) for each cell. Meanwhile $h_{low} = 0.2$ and $h_{high} = 1$. However, to achieve a fair comparison result, we consider two different settings for RIS cells as shown in Figure 8. In the first case, 56 out of 160 cells are in ON states with the shift phase 0° and the rest of them are in OFF states with the shift phase 180° . Meanwhile, the number of ON and

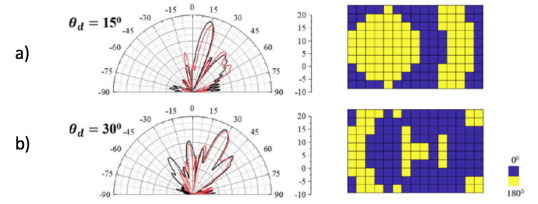


Figure 8: Settings for RIS cells in two cases referred to [8].

OFF states are 48 and 112 cells, respectively in the second case. We refer to [8] for these two settings. For the AE-based modulation scheme, normalization based on average power constraint is used at the receiver block. We first show the constellation diagrams of two modulation schemes using the first RIS setting in Figure 9. The M-PSK scheme distributes symbols evenly on the circle, which means all symbols have the same power. Meanwhile, the AE-based modulation scheme generates symbols with different amplitudes but still guarantees the average power constraint. As a result, the AE-based modulation scheme achieves much lower BLER than M-PSK as shown in Figure 10 for both cases. More specifically, when there are 8 symbols, AE gains roughly 0.5dB than 8-PSK at BLER lower than 10^{-1} in the first case and gains more than 1dB than 8-PSK at BLER less than 10^{-2} in the second case. Intuitively,

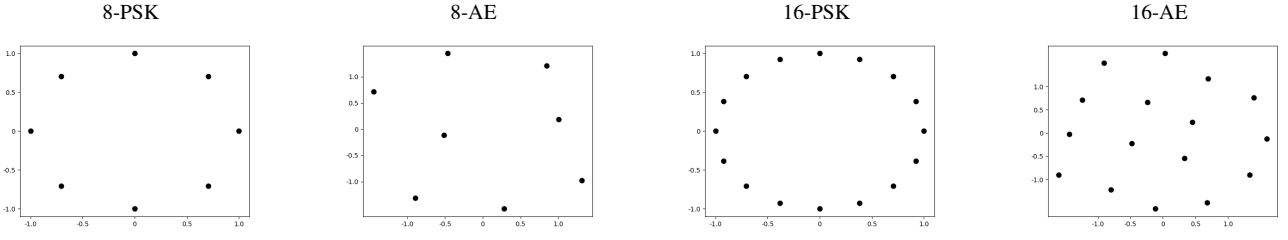


Figure 9: Constellation comparison between M-PSK and AE-based modulation schemes

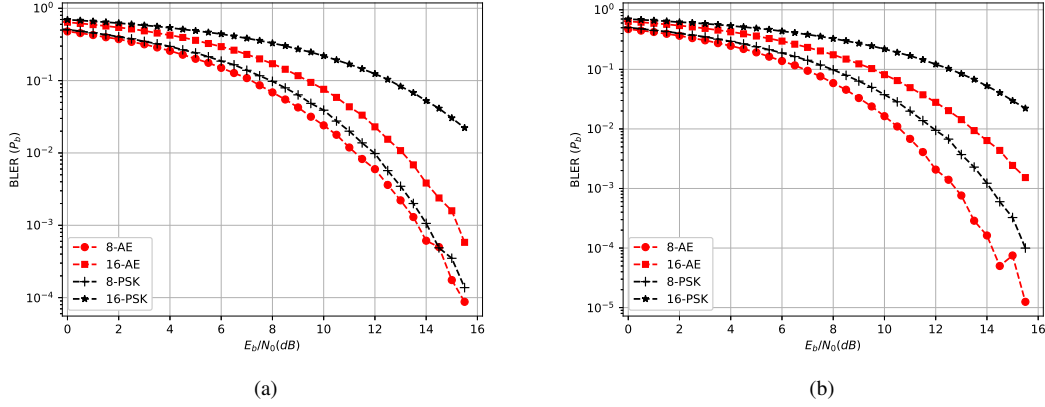


Figure 10: BLER Comparison between M-PSK and AE-based modulation schemes: (a) the first setting for RIS cells and (b) the second setting for RIS cells.

regardless of the RIS cell setting, the higher value of k , the higher gain between these two methods. For example, in the first RIS setting, when $\frac{E_b}{N_o} = 16$ dB and $k = 4$, BLER in the AE-based model is 58 times lower than that in the M-PSK scheme.

5. Discussion

Whenever the accuracy of the communication system is lower than a threshold value, e.g., 99%, we need to check the receiver's location. If the accuracy drop is due to the change in the receiver's position, we need to select a new value for c_{RIS} and then re-train the network parameters of the transmitter and receiver. The training process can be done at a centralized machine and the trained parameters are sent to the transmitter and receiver to update modulation and de-modulation blocks, respectively. Since parameters training usually takes several minutes, the RIS-aided AE-based communication system is more feasible for receivers with low mobility. To support devices with high mobility, several ways can be applied to improve the performance of the system including the increase of transmission power and reduction in the k value.

V. CONCLUSION

In this work, we evaluate the feasibility of an autoencoder-based RIS-supported communication system when there is no light-of-sight path between transmitter and receiver. When the receiver's location and channel state information change, the proposed communication model is more beneficial than the traditional modulation schemes with the fixed constellation diagram. The simulation performance with various parameters proves the potential of the proposed system. In future works, we plan to consider more realistic situations for performance evaluation such as random channel state and far-field communication.

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Chi Hieu Ta received B.E degree with honor in Electronic Engineering in Le Quy Don Technical University in 1994, M.E. degree in electronic engineering in National Defense Academy, Japan in 2002 and PhD degree in signal processing in Strathclyde University, UK in 2008. He is currently working at the Faculty of Radio Electronic Engineering, Le Quy Don Technical University. His research interests include precoding and equalisation for MIMO systems, signal processing for communication and microwave engineering. Email: hieunda@gmail.com



Thi Nga Dao received a B.S. degree in Electrical and Communication Engineering from Le Quy Don Technical University, Vietnam in 2013, an M.S. degree in Computer Engineering from University of Ulsan in 2016, and a Ph.D. degree in Computer Engineering from University of Ulsan, South Korea in 2019. She was a postdoctoral fellow at Intelligent Networked Systems Lab (IN-SLab) of Ewha Womans University from 2020 to 2021. From July 2019, she has been working as a researcher in the Faculty of Radio-Electronic Engineering, Le Quy Don Technical University, Hanoi, Vietnam. Her research interests include machine learning-based applications in communication systems, network security, and network intrusion detection systems. Email: daothinga@mta.edu.vn