Constellation Design With Deep Learning for Down Link Non-Orthogonal Multiple Access

Wireless Communication Project

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Abstract

The Non-Orthogonal Multiple Access (NOMA) is considered a key technology for the next generation of cellular systems. NOMA is expected to meet the rapid increase in the demand of high data rate, massive connectivity, and high reliability for the fifth generation (5G) wireless networks. In downlink NOMA, super-constellation scheme for the transmission is designed by the superposition of the constellation schemes of each individual user. The super-constellation scheme at transmitter end needs to be designed carefully, in order to ensure the complete recovery of data intended for the corresponding receiver. The paper under consideration [1] proposed the novel deep learning based approach that design the optimized constellation scheme for the downlink NOMA. Auto-encoder network is trained in this approach, where Enocder is trained to map data bits to symbol, and Decoder is trained to map received symbol to data bits. The network is trained with synthetic data, and then trained bit to symbol mapping is extracted to get the optimized super-constellation scheme for downlink NOMA. The purposed scheme can be integrated into current communication systems and readily use for a practical purpose. Moreover, the scheme can be readily combined with iterative error-correction devices such as turbo codes or LDPC. Simulation results with synthetic data have verified the effectiveness of this deep learning based approach in designing the super-constellation scheme that allows transmission of data to multiple users simultaneously.

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Chapter 1

Introduction

1.1 Non-Orthogonal Mutiple Access

Non-Orthogonal Multiple Access (NOMA) is one of the most promising radio transmission technique that is expected to meet the rapidly increasing demand for high data transmission rate, massive connectivity, and high reliability for the fifth-generation (5G) wireless networks [2], [3], [4]. The key idea behind Non-Orthogonal Multiple Access (NOMA) is to serve multiple users in the same resource block by exploiting the channel gain differences. In downlink NOMA, signals intended for different receivers are superposed at transmitter end before transmission. Conventionally, the transmitter maps the data bits intended for a single receiver onto the symbol with the help of a constellation scheme. Then this symbol passed through the channel and received at the receiver end. After the reception at the receiver end, the receiver converts this symbol back to the bits with the help of the same constellation scheme. In the case of NOMA, data bits intended for multiple users are mapped on a single symbol. Each receiver has to decode the data bits intended for itself from this single symbol. The super-constellation scheme that dictates the bits to symbol mapping must be carefully designed in order to ensure the exact recovery of data from the single symbol. The distance and channel corresponding to each receiver are not the same. That is why the optimal constellation scheme is crucial for the enhanced performance with NOMA. Generally, Successive Interference Cancellation (SIC) is used at the receiver end. The receiver with high SNR decodes the data after estimating and canceling the signal of weak users, where weak SNR receiver treats the other user signals as interference.

1.2 Deep Learning

Deep Learning (DL) is the branch of Machine Learning that allows the machines to improve with experience. Deep Learning has applied successfully in various fields like autonomous vehicles, speech recognition, computer vision, and reinforcement learning. An autoencoder (AE) is a neural network that consists of two parts encoder and decoder. The encoder is trained to represent data into latent space, and the decoder is trained to recover the same data from this latent space. Recently, Deep Learning has started playing a role in the communication domain, as well. There are many functional similarities between communication blocks and autoencoders. The function of the transmitter is to map data over symbols where encoder also learns to map input over some latent space. On the other hand, the receiver's function is to recover data from the transmitted symbol, where a decoder, like a receiver, learns to recover data from the latent space mapping of encoder input. Many publications have investigated the use of Auto-encoders in the communication domain because of the analogy between Autoencoders and communication systems. [5] demonstrates the ability of a neural network in detecting symbols even when the channel is unknown and non-linear by proposing the algorithm for signal detection for molecular communication. Deep Learning based Orthogonal Frequency Division Multiplexing (OFDM) receiver is proposed that directly recovers transmitted symbols without estimating the Channel State Information (CSI) [6].

1.3 Traditional Approaches of Constellation Design

The super-constellation scheme which is highly crucial for the performance of NOMA is conventionally designed based on off-the-shelf constellation schemes. Several recent publications have investigated these schemes. The superposition of BPSK constellation scheme with equal power allocation factor (PAF) is investigated in [7], and without equal power allocation factor (PAF) is investigated in [8]. Moreover, the superposition of QPSK with PAF policy is proposed in [9]. To exploit the spatial diversity, [10] investigated the angle of rotation of the off-the-shelf constellation schemes. [11] provides the analytical expressions for Bit Error Rate (BER) by optimizing over power allocation and phase rotations without exploiting the labels and possible angle of rotations for BPSK and QPSK. A mutual information based search over optimal PAF policy for two users constellation scheme is proposed in [12], but this search is computationally prohibited. Moreover, Gray mapping technique that proved to be highly efficient in case of traditional schemes, also proved to be efficient with NOMA when receiver decode based on maximum likelihood (ML) method [13].

1.4 Proposed Approach

The optimal constellation scheme for NOMA requires the search over individual constellation schemes, power allocation factors, and angle of rotation. Most of the publications, and approaches separately optimize over each requirement. This paper purposed a novel approach that jointly optimizes these requirements for a super constellation scheme using the power of Deep Learning, specifically Autoencoders. The strengths of the purposed approach are listed below. It does not require to implement SIC at each receiver. The constellation scheme's optimization does not need the analytical expression of the mutual information and prior to the constellation's geometry. The proposed solution can be used in combination with turbo codes or Low-density Parity-Check codes (LDPC) and is fully compatible with already deployed wireless schemes.

The encoder part of an autoencoder learns to map data bits intended for all users to symbols, where the decoder part of each user learns to recover data bits for the corresponding user.

Chapter 2

Methodology

2.1 General Block Diagram

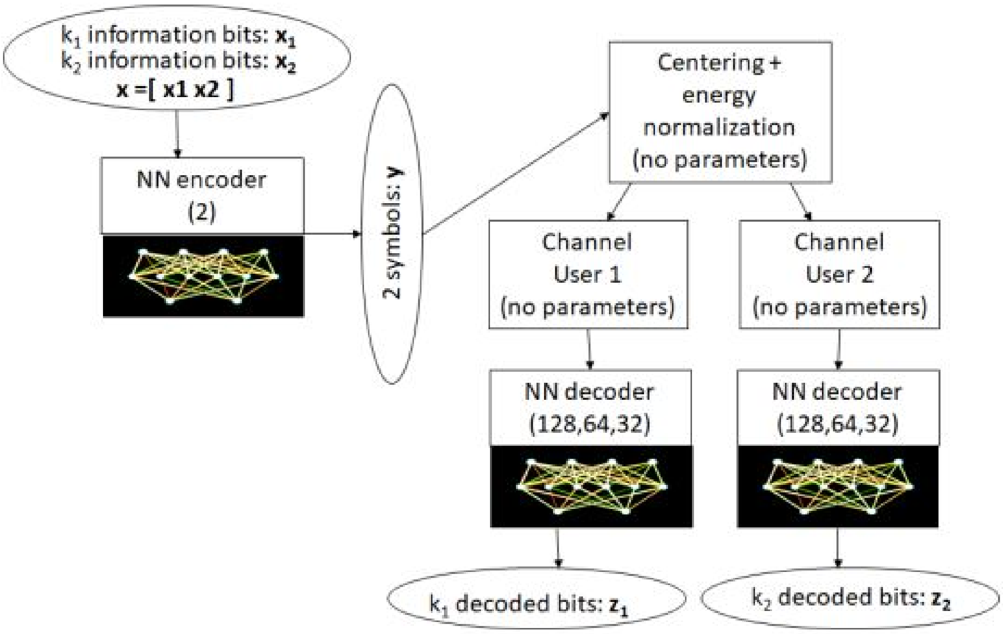

FIGURE 2.1: General Block Diagram

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The Fig2.1 is a general block diagram for the two users. For the sake of simplicity, we start with two users, but the approach can be easily extended to more number of users. Let 'k1' and 'k2' are the numbers of bits per symbol for user 1 and user 2, respectively. First, we concatenate data bits intended for both users, and this vector of size $k = k1 + k2$ is the input vector of our encoder. The total number of constellation points are $2^k = 2^{k1} * 2^{k2}$, because 2^{k1} is the number of possible bits sequence for user 1, and 2^{k2} is the number of possible bits sequence for user 2. Then encoder maps this data vector onto the symbol (or constellation point), where symbol belongs to the complex domain, have both real and imaginary components. So the encoder's output are two values: one corresponds to the real part and the other corresponds to the imaginary part of the symbol. Then to add the power constraint of the transmitter, we add a layer that normalizes the energy in the symbol. To depict the transmission of data from the base station to the user, we add Additive White Gaussian Layer (AWGN) channel layer that randomly applies the noise over the symbol. The channel for each receiver is different because two receivers are at different locations, so the path distance and disturbances are different for each user. Then the decoder of each user recover bits intended for them from the received noisy symbol. 'z1' and 'z2' are the decoded bits by user1 and user 2, respectively.

2.2 Deep Learning Architecture

2.2.1 Encoder

The task of the encoder is to map each bit sequence to a unique symbol (or constellation point), which can be carried out by the linear operation. So, the paper proposed a single layer with a linear activation function, whose input is of size 'k' and output is of length '2'. Then apply the normalization layer just to include the power constraint of the base station.

2.2.2 Decoder

The paper under consideration [1] proposed three layer network for each receiver, where first, second, and third layer have 128, 64, and 32 neurons, respectively. Each layer has a relu activation. The output layer of each decoder depends on the bits per symbol of the corresponding user and have a sigmoid activation function just to limit output between 0 and 1.

2.2.3 Loss Function

An autoencoder is trained to minimize cross-entropy loss

$$L[x, z] = -\sum_{j} x_j log_2 z_j + (1 - x_j) log_2 (1 - z_j)$$

Where $x_j and z_j$ are the transmitted and recovered bit respectively.
In this problem, we try to recover the exact bits that are transmitted. So, our

problem is reduces to binary classification problem, and cross-entropy loss is efficient for this problem.

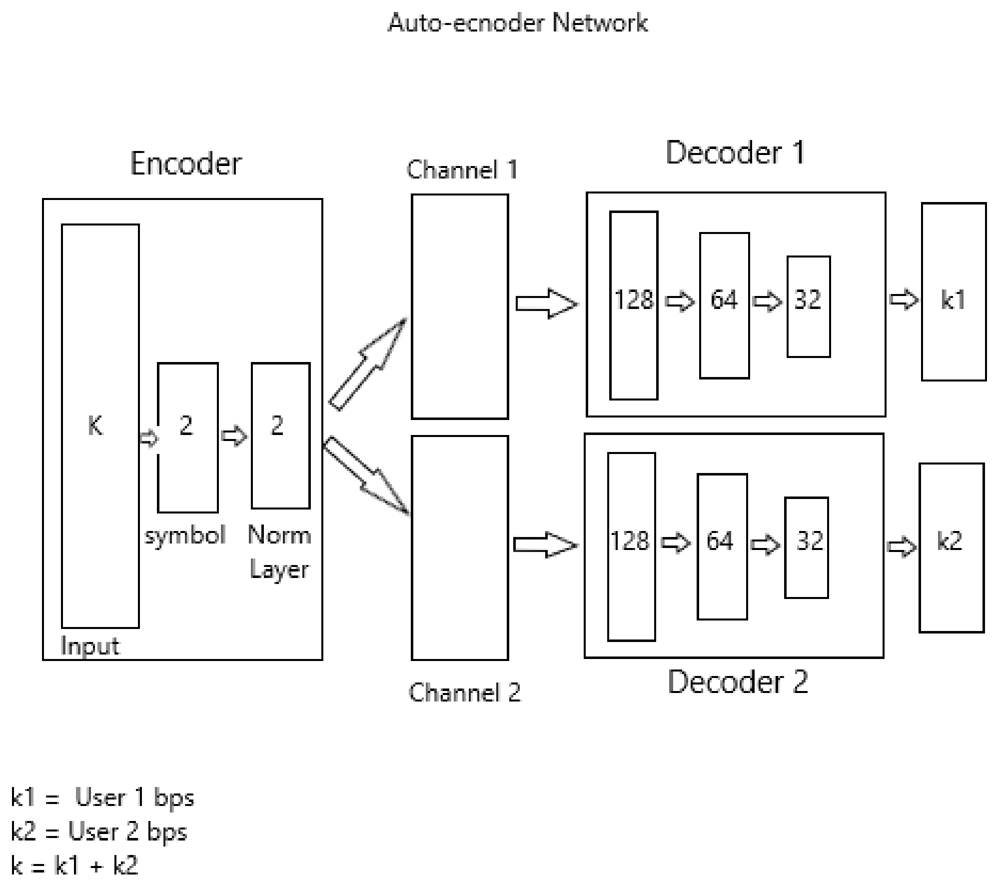

FIGURE 2.2: Deep Learning Architecture

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2.3 Training

The stochastic gradient descent (SGD) is used with learning rate $\lambda = 0.1$ for training. The batch size is 2_k, which contains all possible input bit sequences at the transmitter end. Then the neural network is trained for 50,000 epochs. Usually, by training network for a large number of epochs brings the problem of overfitting. However, this is not the case here because we already have complete information about all possible inputs.

2.4 Extension To More Users

The network discussed above for two users can be easily extended to more users. The encoder part remains the same, only the input of encoder becomes equal to the sum of bits per symbol of each user as we have discussed that each receiver has a separate decoder. So each additional user adds the additional parallel decoder.

This exponentially increases the complexity of the network as well as the optimization time. The number of epochs requires to find the optimal constellation scheme dramatically increases with each additional user.

Chapter 3

Simulation Results

Deep Learning based constellation design approach proposed in the paper under consideration [1] is implemented in python notebook to replicate the results of the paper. Synthetic data is generated using the NumPy library, and Keras is used to build the autoencoder model, which is then trained for 20,000 epochs. The constellation schemes learned by this model for users transmitting simultaneously at the various bits per symbol are attached below.

3.1 User 1 = 1bps and User 2 = 1bps

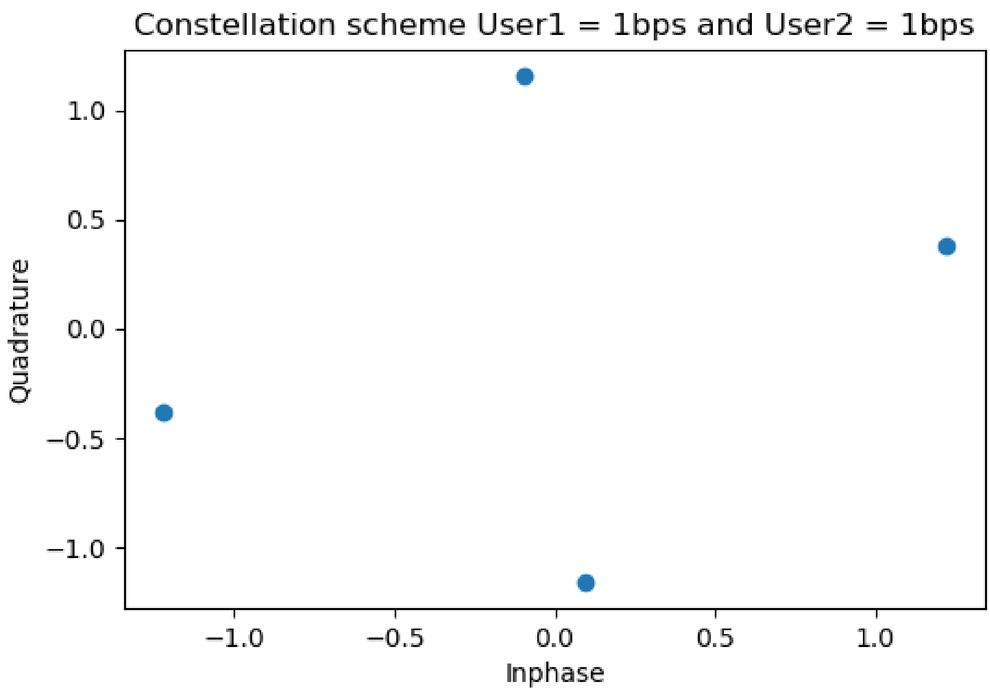

FIGURE 3.1: Constellation diagram for user 1 = 1bps and user 2 = 1bps

The Fig3.1 is the Constellation diagram learned by the model for two users. Both User 1 and User 2 are transmitting at 1 bit per symbol (bps). Here k1 = 1, and k2 = 1 so the total number of constellation points must be $2^{k1+k2} = 4$ to uniquely represent each possible bit sequence. The learnt sequence is very much like the QPSK scheme, but model also optimize over angle of rotation. Because unlike traditional approaches, model jointly optimize over constellation scheme as well as spatial diversity.

3.2 User 1 = 2bps and User 2 = 1bps

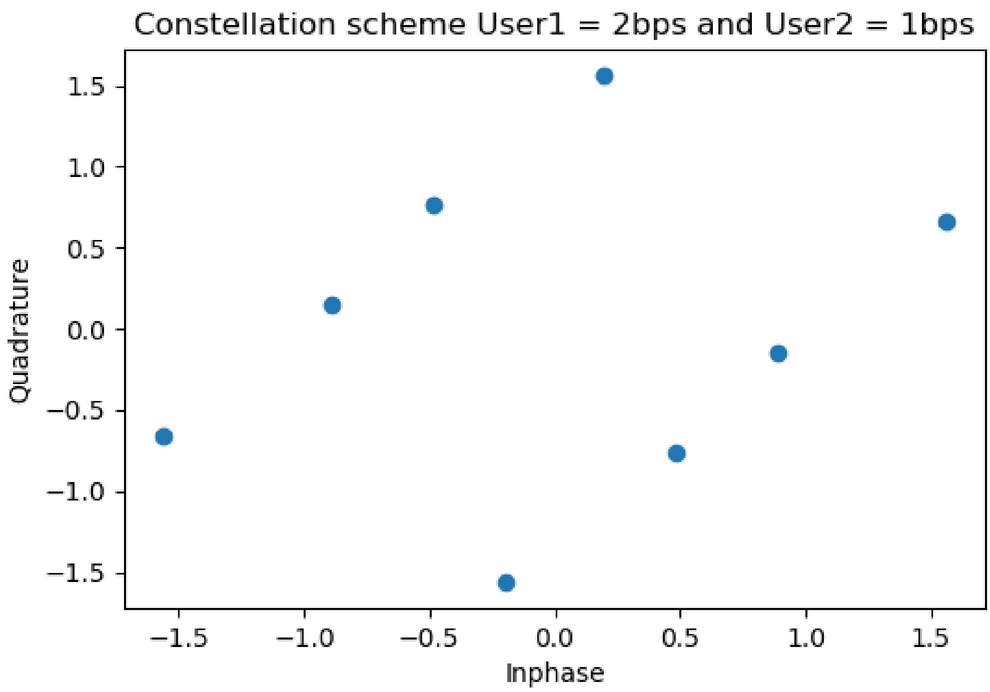

FIGURE 3.2: Constellation diagram for user 1 = 2bps and user 2 = 1bps

The Fig3.2 is the Constellation diagram learned by the model for two users. Where User 1 is transmitting at 2 bps, and User 2 is transmitting at 1 bps. Here k1 = 2, and k2 = 1 so the total number of constellation points must be $2^{k1+k2} = 8$ to uniquely represent each possible bit sequence. The learnt sequence is very much like the superposition of BPSK and QPSK schemes, only it rotated around 45^o. This is the power of deep learning model rather than just selecting the optimized constellation scheme, model also tries to optimize over power allocation policy, and also exploit the spatial diversity in finding the super-constellation scheme for transmission.

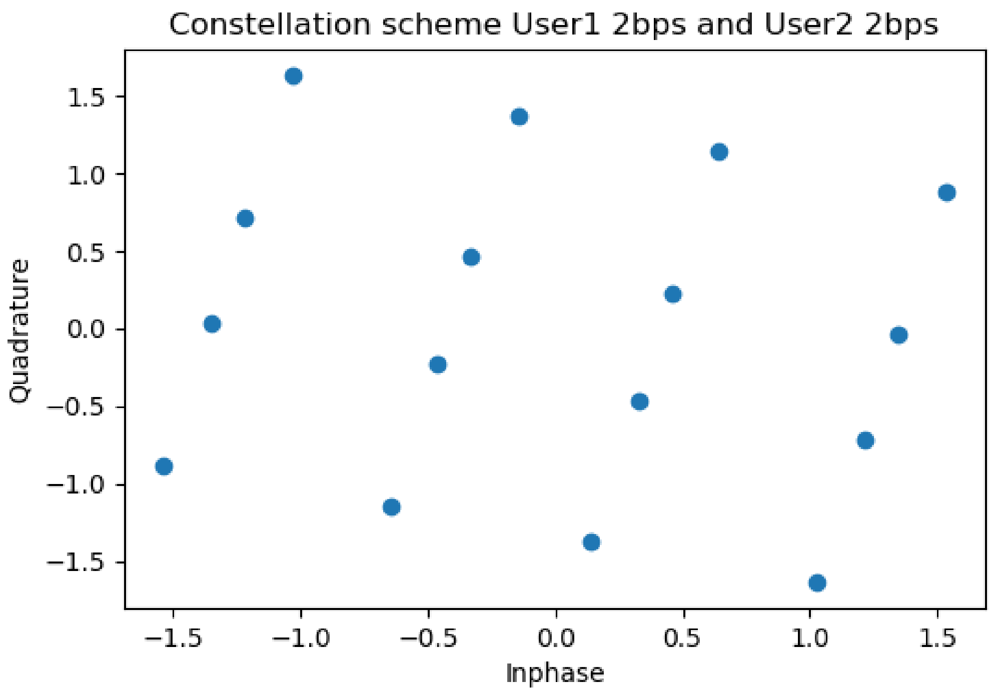

FIGURE 3.3: Constellation diagram (user 1 = 2bps and user 2 = 2bps)

3.3 User 1 = 2bps and User 2 = 2bps

The Fig3.3 is the Constellation diagram learned by the model for two users. Where User 1 is transmitting at 2 bps, and User 2 is transmitting at 2 bps. Here k1 = 2, and k2 = 2 so the total number of constellation points must be $2^{k1+k2} = 16$ to uniquely represent each possible bit sequence. The learnt sequence is very much like the superposition of two QPSK schemes, only it is slightly rotated around -30^o. Like previous optimized constellation schemes by model, this constellation scheme also exploit the spatial diversity in finding the super constellation scheme.

3.4 User 1 = 3bps and User 2 = 1bps

The Fig3.4 is the Constellation diagram learned by the model for two users. Where User 1 is transmitting at 3 bps, and User 2 is transmitting at 1 bps. Here k1 = 3, and k2 = 1 so the total number of constellation points must be $2^{k1+k2} = 16$ to uniquely represent each possible bit sequence. The learnt sequence is very much like the superposition of two QPSK schemes, only it is slightly rotated around 45^o.

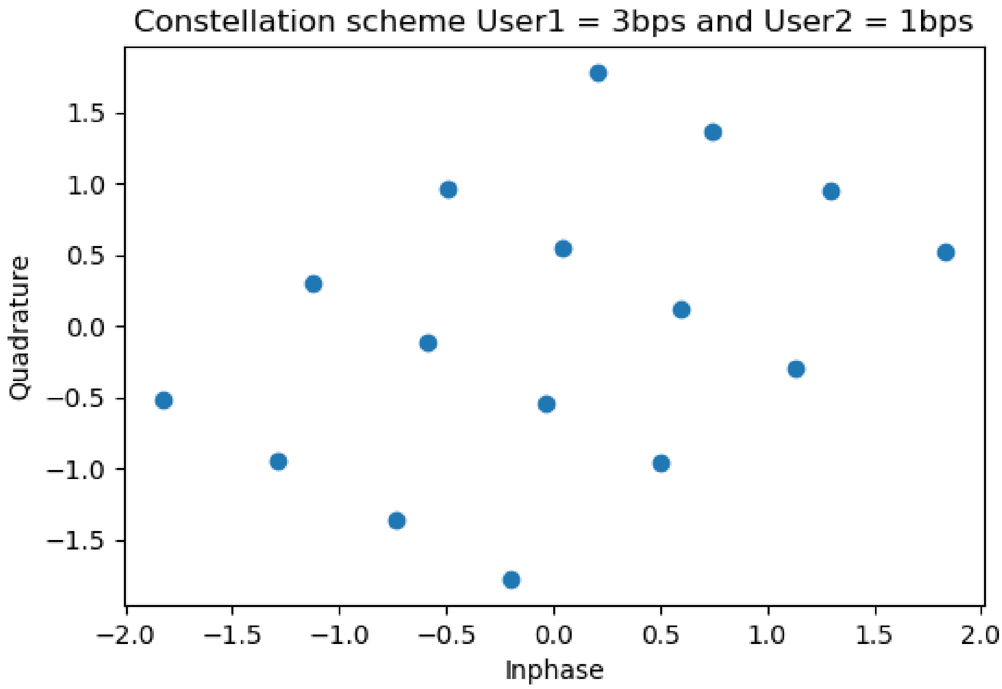

FIGURE 3.4: Constellation diagram (user 1 = 3bps and user 2 = 1bps)

3.5 User 1 = 3bps and User 2 = 2bps

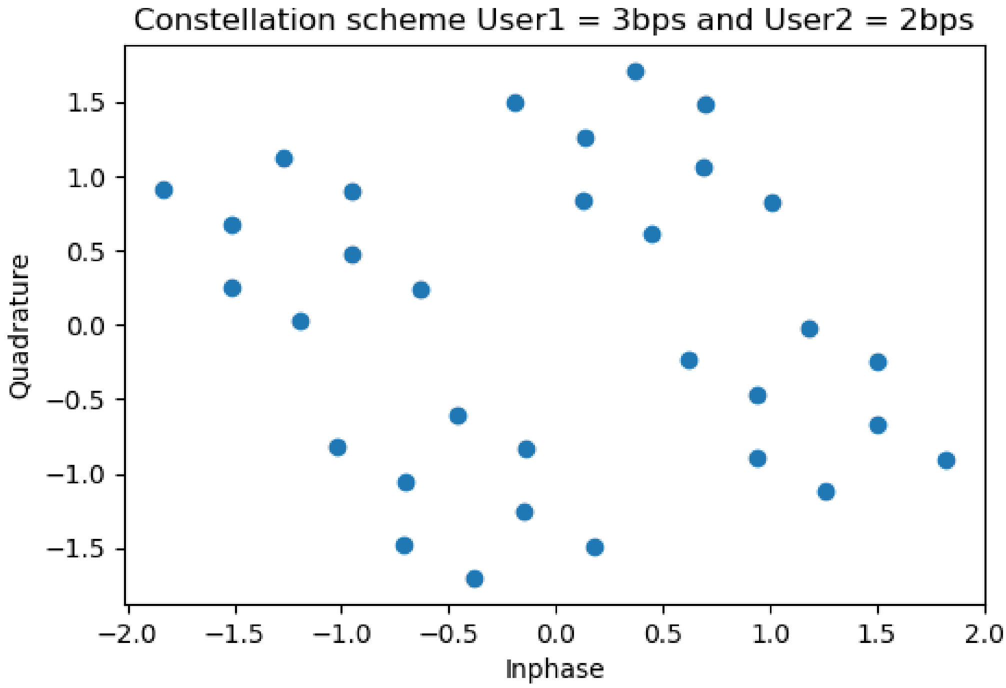

FIGURE 3.5: Constellation diagram (user 1 = 3bps and user 2 = 2bps)

The Fig3.5 is the Constellation diagram learned by the model for two users. Where User 1 is transmitting at 3 bps, and User 2 is transmitting at 2 bps. Here k1 = 3, and k2 = 2 so the total number of constellation points must be $2^{k1+k2} = 32$ to uniquely represent each possible bit sequence. The learnt sequence is very much like the superposition of two QPSK schemes and a BPSK scheme. In optimizing constellation scheme, model exploited the spatial diversity and constellation scheme, in this way that each block of four constellation points has different angle of rotation.

Now, after viewing the super-constellation schemes generated by the proposed auto-encoder model, you can notice that generated schemes are very much similar to the off-the-shelf schemes that are used in practical communication systems. The deep learning model generated all these similar schemes without any prior information about the present scheme. Moreover, the model also exploits the spatial diversity in the form of the angle of rotation, and distance from the zero.

3.6 Bit Error Rate Analysis

To check the validity of the optimized schemes through the proposed model, and to compare our results with the paper under consideration [1], I have plotted the Bit Error Rate (BER) vs SNR graph for each scheme.

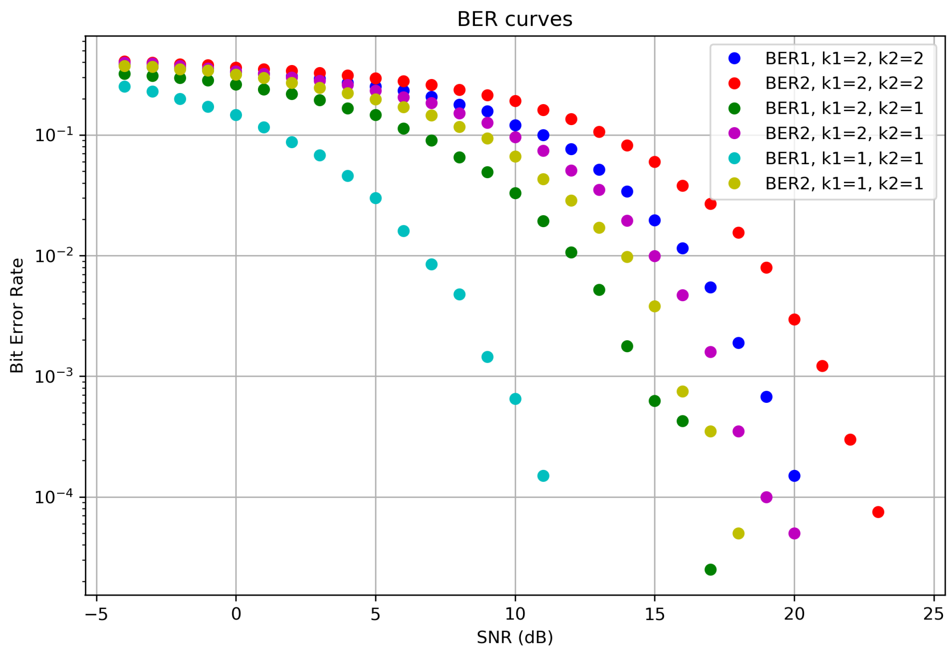

FIGURE 3.6: BER Curve

The Fig3.6 is the BER vs. SNR plot. For this figure, I have randomly picked 20,000 test bit sequences and then passed through the encoder to get their symbol representation, which is in accordance with the generated constellation diagram. After that, to depict the transmission from the base station to the user, I apply the AWGN channel separately for each user. In this testing, user 1 is considered a high SNR user, and user 2 as a low SNR user. The difference between their SNRs is 9dB. Some key observations from the graph are (1) BER curve for user 1 (high SNR) is always less than the user 2 (low SNR). (2) BER curve shifted upwards by increasing the number of bits per symbol for both users, which is also true in the case of the practical systems. The BER exponentially decreases with the increase in SNR and becomes almost negligible at around SNR of 23 dBs. However, this depends on the hyperparameter, the channel SNR we use at the time of training, and the number of epochs. However, the BER curve trend validates that the approach proposed in this paper indeed provides promising results.
The generated constellation schemes and BER curves are very similar to those provided in the paper [1] following for the project.

Chapter 4

Project Implementation

4.1 Conclusion

The validity of the proposed deep learning based constellation design for non-orthogonal multiple access (NOMA) has established in this article. Auto-encoder trains to jointly optimize over constellation schemes, spatial diversity, and power allocation policy, rather than optimizing over them individually. There is no need for analytical expressions for bit error rates, and computationally expensive search to maximize mutual information. The scheme also encompasses all possible users configuration, because it does not assume any information about the position of users with in the cell. The generated super-constellation schemes can be readily integrated in the practical communication systems. Moreover, scheme can also be joined with the off-the-shelf error correction techniques such as turbo codes, and LDPC.

4.2 Future Recommendation

Train encoder and decoder model of the network on real life data. This article optimized their deep learning model using synthetic data. Implement Encoder and Decoder on two separate machines and then set up a communication link between them with the help of Software Define Radios (Radios) such as USRPs. In this way, model trains over actual wireless channel, and able to observe real life channel impairments. This application provides more robust and more generalized encoder and decoder model than the proposed approach for the practical wireless communication.

Optimization of an auto-encoder model by including path loss models and assuming various channel fading such as Rayleigh, and Nakagami fading. The proposed article works with the most basic AWGN channel. The practical channel is not

that simple, channel have some kind of delay spread, have some Doppler profile, and shadow fading. To develop a model that works in real world, training must incorporate these characteristics during optimization.
Application in the domain of data compression. In this article, we observe that the encoder maps bits to symbol, where number of bits can be greater than 2, where size of a symbol is 2. Decoder able to recover the mapped bits from the symbol even after the addition of noise. This system can be easily used in the application of data compression where encoder is trained to map bits into some latent space whose vector size is less than the number of bits for the purpose of compression, and decoder is trained to recover the data from the latent space. Same model provided in this article does not able to fulfil this compression, but the simulation results have shown some validity in this approach. Research have to be conducted to find the efficient encoder and decoder structure, and optimal loss function.

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