IMPLEMENTATION OF MIMO-NOMA USING A DEEP LEARNING APPROACH

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Abstract— Non-orthogonal multiple access (NOMA), is one of the significant candid approach for the Fifth-generation (5G) has drawn a great deal of attention in the wireless communication. At receivers, previously Successive interference cancellation (SIC) technique was utilized most commonly for both uplink and downlink of NOMA transmission, which complicates the receiver and raises issues with error propagation limit. In order, to avoid complications faced we investigate a tool with excellent performance and efficiency i.e, Deep Learning(DL). This approach analyses automatically the channel state information (CSI) and detects the original transmission sequence. The ideal channel gain in the present schemes, can be achieved by removing the signal which has a greater power allocation factor while detecting the signal with a lesser power allocation factor. In a Proposed model of Deep Learning both channel estimation process recovers the signal facing the channel distortion and multiuser signal superposition. Simulations of MIMO-NOMA-DL systems have been analyzed and compared to the previous SIC method. This approach successfully construes channel impairment and obtains a good detection performance, according to the findings of our simulations. Instead of employing clever detection methods, MIMO-NOMA-DL uses a neural network to find the best answer (NN). Deep learning is therefore a strong and useful tool for NOMA signal detection.
Keywords— 5G, Deep-Learning, Multiple Input Multiple Output, Non-Orthogonal Multiple Access, Wireless Communication

Introduction

As the need for data is increasing day by day in this scenario every generation in cellular communication systems turn up with new standards, schemes, and features in such a way owing for betterment compared to the previous ones.

For the effective usage of the available spectrum to attain high system throughput and latency significantly Multiple access techniques are used. It is one of the core components of wireless communication networks. By using Multiple access techniques several users could partake in a single radio resource for communicating to the base station (BS). The various access techniques are Time Division multiple access (TDMA), Frequency Division multiple access (FDMA), and Code Division multiple access (CDMA) which were frequently employed in previous generations of cellular networks. These methods are known as Orthogonal multiple

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access (OMA); users have orthogonal access so that they do not interfere with the other while being in a common channel for communication. The mentioned schemes assign multiple users with orthogonal radio resources in the time, frequency, or code-domain, or combinations.
In TDMA, each user is assigned a dedicated time slot for transmitting signals. Thereafter, the signals are differentiated at the receiver end according to the time slots correspondingly. In the same way, FDMA takes the available spectrum and divides it into a various number of non-overlapping subchannels based on frequencies, of which each is assigned to an individual user, allowing multiple users to use channels simultaneously which are differentiated according to the frequency at the receiver.
In contrast to FDMA, TDMA the CDMA uses a distinct orthogonal spreading technique which optimizes the use of available spectrum and transmits over it by using the same resources. At the receiver end, the user signal is differentiated using decorrelation, which distinguishes the intended user's signal from other signals by utilizing the unique code issued to it. A low-complexity receiver may often be utilized to detect the intended user's signal in OMA-based systems since, it is hypothesized, orthogonal resource allocation prevents interference between users in these systems. OMA systems cannot sustain the large number of users required for 5G due to insufficient resources.
NOMA, in contrast to OMA, permits user interference in the distribution of resources, allowing numerous users to share a single resource block. This in reality causes interference; cancellation techniques like successive interference cancellation (SIC), are used to mitigate the effect. It has been shown that NOMA is capable of handling large connections with improved total capacity and user fairness. MIMO-NOMA can increase communication system throughput with the benefit of MIMO technology.

Fundamentals Of NOMA

NOMA is one of the most promising techniques in the Fifth generation of wireless communication which has more potential compared to Orthogonal Frequency Division Multiple Access(OFDMA). It offers enhanced spectrum efficiency and is highly reliable by reducing latency.
NOMA can be classified into three types: NOMA power domain, NOMA code domain, and NOMA hybrid domain[2]. This paper, we concentrate on the Power domain NOMA for downlink MIMO systems because of the typicality and representativeness of NOMA techniques[2]. The result of the article can provide guidance to delve deeper into more complex NOMA techniques.
To date, the maximum customary technique for signal detection of MIMO-NOMA is SIC A multi-user signal is first multiplexed in the downlink using superposition coding at the bottom station under a strict energy limit. Channel impairment at the receiver will trigger the SIC process, which will decode the projected sign based on the clustering of user equipment (UE) channel profitability. While the UE sign with the lesser energy allocation is treated as interference, the UE sign with the lower channel benefit is given higher transmit energy and decoded first. After the sign with higher energy is identified and decoded, reconstruction of the

modulated signal is executed which is subtracted from the acquired signal. The procedure is maintained till the UE can decode its needed data. From this perspective, SIC is the most useful multiple-get right of entry to the scheme in phrases of the attainable multi-user ability location in each uplink as well as downlink.

Rather than the classic SIC method, we use the Deep-learning Neural Network (NN) for detecting MIMO-NOMA signals. DL being a part of machine learning, DL has made significant progress in recent years and is applied in many fields. The main developments of deep learning are mainly related to deep neural networks (DNNs) in classification and pattern recognition, normal neural networks (CNNs) in image processing, and recurrent neural networks (RNNs)) in speech recognition for natural language processing (NLP)[2]. Deep. Powerful Performance Learning has dramatically changed our daily lives and the perception of artificial intelligence (AI).

Remember that while consumers still have to pay for some graphics processing unit (GPU) resources, Moore's Law states that costs have been steadily decreasing in recent years. There are always new items coming out with better performance and lower prices. Google proposed Tensor Processing Units (TPUs) in 2016, a processor specifically for AI ASICs. According to the report, the price of the third generation TPUless than 80%. We believe that the age of AI has arrived.

Although there are not many successful commercial applications of deep learning in wireless communications, many researchers are working to integrate machine learning techniques into communication systems, especially to improve current signal processing algorithms. Deep learning can be used to learn a channel decoding method instead of a simple classifier. Successful applications include improving confidence propagation (BP) decoders to produce better bit error rates for linear and polar codes. Performance for throughput (BER) with low complexity In terms of recovery quality and computation time, compression sensors (CS) based on deep learning theory can outperform modern CS methods. Classification and identification of modulation based on deep learning is another highly appreciated area.

Mimo-Noma and Deep Learning

Transmission and the conventional SIC algorithm in the next, can analyze the basic architecture of deep learning. For simplicity, we assumed a bandwidth of 1 Hz. Channel impairments include Rayleigh fading channels and additive white Gaussian noise (AWGN) channels.

The basic principle for NOMA transmission and the traditional SIC algorithm are discussed in this part. The fundamental structure for deep learning is then examined. We used a frequency of 1 Hz for the sake of simplicity. Rayleigh fading channels as well as additive white Gaussian noise (AWGN) channels are examples of channel impairments.

Basics Of MIMO-NOMA

NOMA can implement multiple signal multiplexing by allocating single-ended power within the same time/frequency/code resources. Unlike traditional orthogonal multiple access (OMA), which uses orthogonal resources such as OFDM, NOMA uses power in a non-orthogonal fashion to greatly improve spectral efficiency at the expense of receiver complexity. Fig. 1 shows the overall architecture of a basic NOMA system

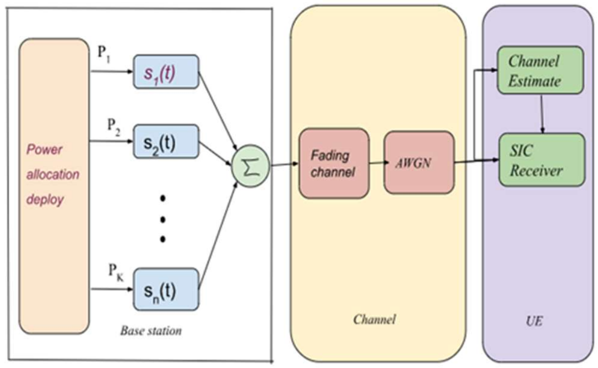

Fig. 1. Architecture of Non-orthogonal multiple access (NOMA) system

The majority of the time, UEs which are used for traditional downstream multiuser MIMO occupy orthogonal resources. When the wide variety of BS transmitting antennas are greater than that of receiving antennas, interbeam interference can be completely eliminated. However, in MIMO-NOMA systems, there are always more user UE antennas than transmitting antennas, so clusters must be shared among UEs. Therefore, it is imminent that other UEs in the same cluster causes interfere. Beamforming technology allows BS antennas to transmit different beams in different directions. Yet, clusters must be shared across UEs in MIMO-NOMA systems as there are often more UE antennas than that of transmitting antennas.

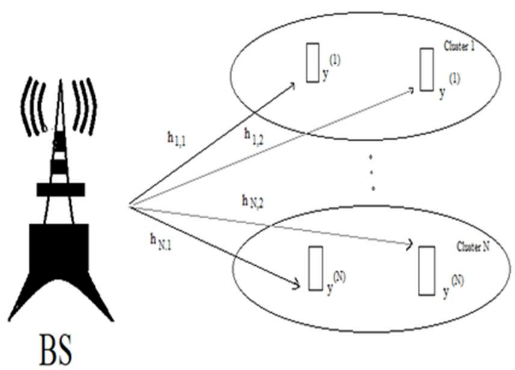

Fig. 2.Block Diagram of Multibeam MIMO-NOMA

Consider N users in a cluster, Bj(t) denote the j-th UE signal at the BS,(j = 1, 2,....., N). The Power which is allocated to user j is represented as Pj, which is limited by the transmission power

Total Power is summated as P = p1 + p2 +.... + pN and Transmission signal can be denoted as below

$$s(t) = \sum_{j=1}^{n} \sqrt{P}jBj(t) \quad (1)$$

A received signal through fading channel and AWGN channel can be expressed as below

$$s(t) = h(t) * \sum_{j=1}^{n} \sqrt{PjBj(t)} + n(t) \quad (2)$$

SIC method was usually adopted for detection of NOMA earlier and was an optimal multiple-access scheme as it has a multiuser capacity region on both downlink and uplinks.

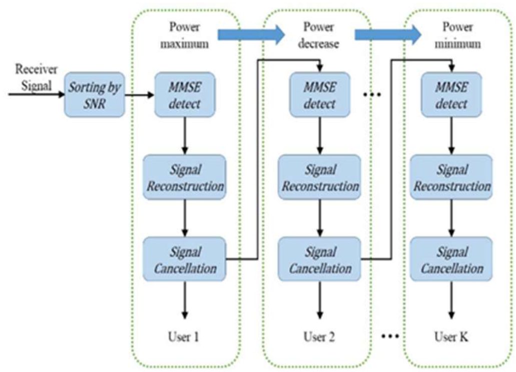

Fig. 4.Architecture of SIC Receiver block

SIC process in the receiving end follows descending order of SNR, as P1 > P2 >.... > PN, User1 is decoded here considering remaining signals as a noise. Total throughput of the signal can be given as below:

$$R_1 = \log_2\left[1 + \frac{P1|h1|2}{\sum_{i=2}^{N} P1|h1|2 + X0}\right] \quad (3)$$

$$R_N = \log_2\left[1 + \frac{P1|h1|2}{\sum_{i=K+1}^{N} P1|h1|2 + X0}\right] \quad (4)$$

Throughput for N users is

$$R_N = \log_2\left[1 + \frac{PN|hN|2}{Xo}\right] \quad (5)$$

The lower-power signal's decoding accuracy is impacted by the higher signal's accumulated decoding error which is one of the major issues with the SIC method which needs to be eradicated.

Basics Of Deep Learning

One of the machine learning approaches called "deep learning" trains the computer to anticipate results from a given set of inputs drawn from a number of layers.
The fundamental methods of deep learning include DNN, CNN, and RNN. Whereas DNN is more sophisticated and has three layers—input, output, and hidden—instead of two, depending on the complexity of the signal processing method. Each layer is made up of several nodes that influence the layers below it. The graphic below depicts the DNN construction model.

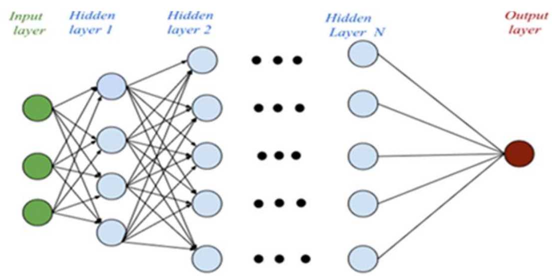

Fig. 4. Structure of Deep-Neural-Network

Adjacent layers have two component relations one is linear and the other is non-linear. Whereas linear component leads to a linear relation between the input as well as output of each layer. It consists of two types of operations where w-weight represents multiplication and b-bias represents addition. But the majority of real-world situations involve nonlinear issues that the linear approach cannot resolve. The activation function f (.) is used to handle the nonlinear component as a result.
Considering (n-1) layer output as yn-1 and nth layers wn as weight matrix and bn as bias vector and output is denoted as shown in the equation

$$y_n = f(w_n y_{n-1} + bn) \quad (6)$$

The sigmoid function is a traditional DNN activation function (7). The function's range is restricted to [0, 1], and it can roughly express the probability. Another traditional activation function is the tanh function (8). The center of each layer's output is 0 and the tanh function's range is expanded to [-1, 1], causing stochastic gradient descent to converge more quickly (SGD). The rectified linear unit (ReLU) function is a further potent activation function (9). The ReLU function does not limit the value to [0, 1] or [-1, 1], but instead grows linearly at x >= 0 and reaches zero at x 0. Even after numerous nonlinear processes, the gradient remains same.

$$F_{sig}(x) = \frac{1}{1+exp^{x}} \quad (7)$$

$$\tanh(x) = \frac{e^{x}+e^{-x}}{e^{x}-e^{-x}} \quad (8)$$

$$\mathrm{ReLU}(x) = \begin{Bmatrix} x, x > 0 \\ 0, x < 0 \end{Bmatrix} \quad (9)$$

The transmission expression for the numerous hidden layers can be defined as follows, assuming that the bias is set to zero for simplicity.

$$\mathbf{y_n} = f(w_n f(w_{n-1} f(w_2 f(w_1 y_0)))) \qquad (10)$$

The sigmoid function as defined in (7) and the softmax function are the two most widely used options for the output layer. The softmax function, which is mostly used for multiclass classification, is described as follows:

$$f_{soft}(x)_i = \frac{exp\ (xii)}{\sum j\ exp\ (xjj)} \qquad (11)$$

Deep learning algorithms are frequently required to provide the system with a huge quantity of data, and this is a training set, in order for them to adjust to ideal conditions offline. During the training phase, the output must be corrected using accurate data. The input and output can then be connected for monitoring purposes. An algorithm trained on this test set can be used to assess DNN performance. In DL, especially in the field of machine learning, CNNs are extremely important. Contrary to traditional NNs, CNNs have a structure that is very different. LeNet-5 is the traditional CNN shown in Fig. 5. Layer S2 is a pooling layer, Layer C3 is still another convolutional layer, and Layer C1 is a convolutional layer. The S4's pooling layer

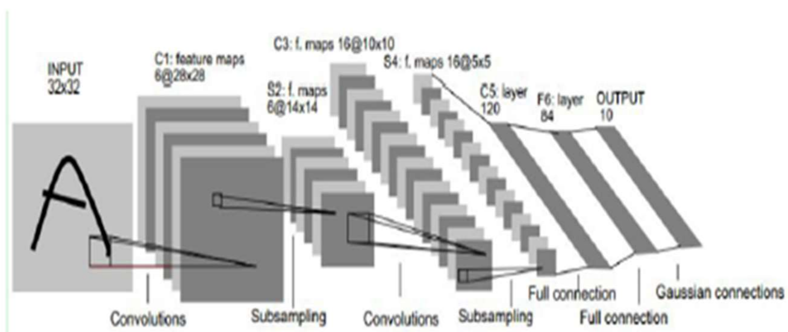

Fig. 5.Architecture of LeNet-5

Before the fully linked layers, the input data is evidently processed via a number of layers of convolution and pooling. Using a convolutional layer composed of many feature maps can significantly minimize the number of connections in a convolution process. Local data can be further compressed by downsampling layers, also known as pooling layers, and overfitting problems can be avoided. The most common methods for collecting the mean and max values from the output of convolutional data are referred to as Max-Pooling and Mean-Pooling, depending on the pooling size.

Due to their capacity for data storage, RNNs are another NLP research hotspot. RNNs may handle scenarios where distinct sequences of slots are related to one another by building link between the current and the past (and potentially the future) data. Fig. 6 illustrates the RNN's fundamental structure. As you can see, status is a summary of the data from Previous information Wk(t) to calculate the output y*(t) using present input x(t). The output number from the RNN can vary from the input number for different purposes, such as one input for multiple machine translation outputs, many inputs for one mood classification output, and so on.

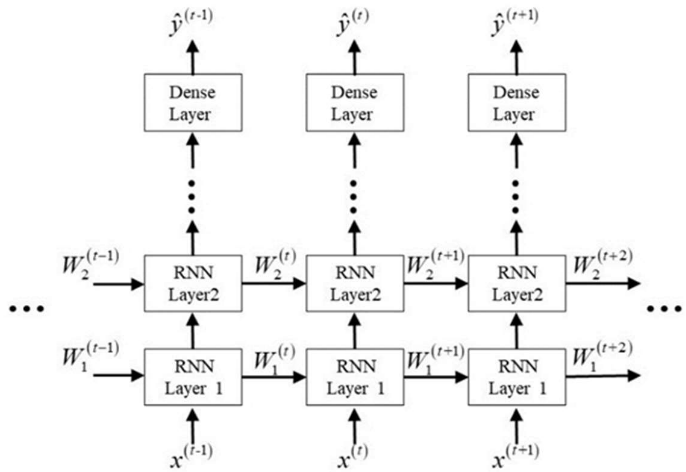

Fig. 6. Model of Recurrent neural network (RNN)

Mimo-Noma Systems-Based on Deep learning schemes

In wireless communication, signal detection may be viewed as a classification procedure that extracts a unique sequence from the signal that has been tampered with. This problem can be effectively resolved using the DL strategy. Therefore, we examine a new DNN-based detector for MIMO-NOMA systems in this part. Contrary to the standard SIC, which divides the detection method into discrete blocks, the deep learning approach is capable of performing all of these operations as a single process. These operations include signal evaluation, demodulation, channel decoding, MMSE sensing, and channel sensing. By constantly iterating, the best parameters may be obtained and rules governing how the output and label matches.

Assesment Of DL in MIMO-NOMA Systems

In this assessment of DL, first detect the MIMO-NOMA signal instead of a SIC receiver. Let us consider the transmitting antenna's number to be T and the receiving antenna's as R. The number of UEs is N. The MIMO-NOMA transmission signal in (1) can be expressed in the form of matrix as (12):

$$X=(X_1,X_2,\ldots,X_T) \quad (12)$$

XT(t ∈ [1, T]) is the t-th transmitting antenna and it is be represented as shown:

$$X_T=\sum_{k=1}^{N}\sqrt{Pk}\quad X^{K}_{T} \quad (13)$$

The Nth UE transmission signal of the Tth antenna is represented by XkT ∈Si in the M-ary phase shift keying (MPSK) modulation, where Si is the collection of T transmitting signals:

Si=Aexp(i*wt*+φ_j)(*j*=1,2,....,T) (14)

For improving the channel capacity, MIMO-NOMA signal uses the power dimensions. So, that Connectivity matrix is doted by the 3rdorder tensor H ∊ RTxRxK. hkTR (k∊ [1, K],r ∊ [1, R] and

t ∊ [1, T]) is the channel gain of the kth UE from the Tth transmitting antenna to the Rth receiving antenna.

$$H = \begin{bmatrix} \begin{bmatrix} h_{11}^1 & h_{12}^1 & \cdots & h_{1M}^1 \\ h_{21}^1 & h_{22}^1 & \cdots & h_{2M}^1 \\ \vdots & \vdots & \ddots & \vdots \\ h_{N1}^1 & h_{N2}^1 & \cdots & h_{NM}^1 \end{bmatrix} & \begin{bmatrix} h_{11}^2 & h_{12}^2 & \cdots & h_{1M}^2 \\ & & & h_{2M}^2 \\ & & & \vdots \\ & & & h_{NM}^2 \end{bmatrix} & \cdots & \begin{bmatrix} h_{11}^K & h_{12}^K & \cdots & h_{1M}^K \\ & & & h_{2M}^K \\ & & & \vdots \\ & & & h_{NM}^K \end{bmatrix} \end{bmatrix}$$

Transforming the tensor H into a matrix H(n) is called the node-n matricization. Here, a mode-3 matricization H(3) can be expressed as above.

Mimo-Noma -DL System

To overcome the shortcomings of SIC receivers, the simplest and most efficient MIMO NOMA DL scheme is proposed using a novel DL detector for MIMO NOMA signal detection. The received signal from the receive antenna can be sent directly to MIMO. NOMA-DL detector without additional signal processing,

MIMO-NOMA-DL system consists of three components:

(a) Training block

(b) Testing block

(c) DNN detecting block

The building block of MIMO-NOMA-DL model in Fig. 7 labels are given to each DNN by the training block to generate a MIMO-NOMA signal. For each antenna two training sequences of UE1 and UE2 are generated to acquire a MIMO NOMA signal. Transmitting signals are modulated by superposition coding scheme by varying power factors and lesion signal at receiver by fading and AWGN channel. The received sequence is known as a label which is similar to the pilot sequence.

Coming to the testing part a real-time transmission of MIMO-NOMA is simulated and labels are not a part of this. In this Performance of the DNN detection is infringed.

In particular, to avoid perfect matching, the channel models and generated data for the training and test blocks i.i.d. ensure that the DNN performs well during both the training as well as testing processes. SNR of Training block is randomly generated with respect to time whereas Test block is fixed so, that error performance of DNN under various circumstances could be evaluated.

For decoding the received signal DNN block is used. The channel characteristics and MIMO-NOMA decoding algorithm can be studied by optimizing the hyperparameters of the deep neural network. Several parameters must be designed in this block, including the number of layers, activation function, loss function, and optimization criterion iterative algorithm; details are covered in the next subsection.

The first two blocks provide the contaminated records and signals of the channel, and the last block restores the original data. Therefore, the identification process can be divided into two steps:

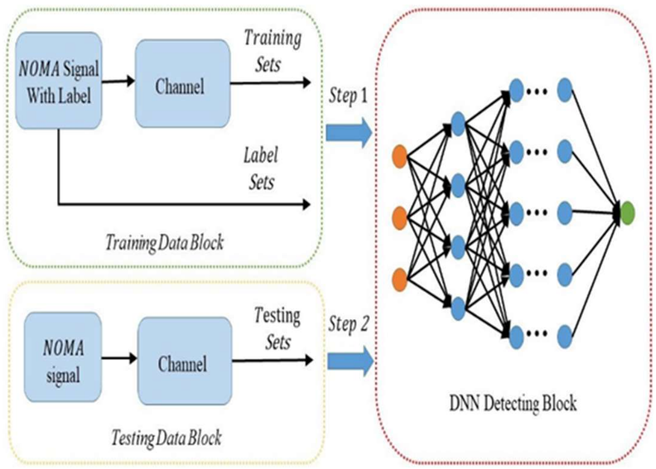

Fig. 7. Block diagram of the MIMO-NOMA-DL model.

DNN Design

DNNs are the deep version of neural networks. Customizable hyperparameters embrace weights, regularization parameters, learning rate, dropout and biases. Designed DNN model for detection of downlink of MIMO-NOMA has seven layers: input layer,output layer, and hidden layers. Hidden layers and input are connected and output layer forms various groups accordingly to decode signals from multiple antennas in a single slot.

First MIMO NOMA signal is received by the input layer. Let the numbers of transmitting and receiving antennas of Base Station and User equipment are Nt and Nr, respectively. The received complex signal is later on decomposed into the real and imaginary parts, so that number of input layer cells becomes 2Nr. A slot and several antennas make up the two-dimensional vector of the input signal. In other words, the 2Nr data are transmitted to the network as a column vector in a single slot.

Five completely connected layers make up the hidden layers. The ReLU function (9), an efficient nonlinear function, is employed to activate the neurons after the linear operation in order to circumvent the vanishing gradient problem of the sigmoid function. The final detection results are reported using the output layer. The typical DNN output layer typically uses one-hot encoding using the softmax function and is fully linked. However, signals from many antennas should be decoded in a single slot in MIMO-NOMA signal detection. In order to form groups, the proposed output layer was created. The number of neurons in each group is equal to the number of one-hot encodings, and the number of groups is equal to the number of transmitting antennas Nt. Fig. 8 depicts, as an illustration, the output layer structure of a 4X4 MIMO-NOMA system. The output data adopt the soft-decision form with the sigmoid function(7) because the label is not in the conventional form but rather uses group one-hot encoding .

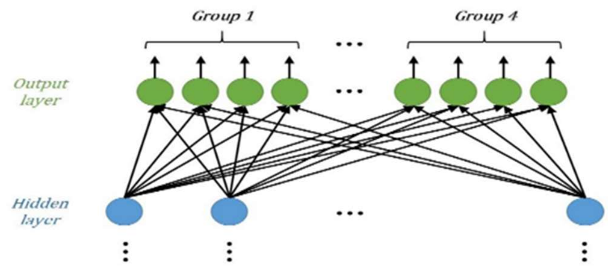

Fig. 8. Model of Output layer.

Crucial component of the MIMO-NOMA-DL network is the selection of the loss function and optimization technique.
MSE has a poor convergence speed in multiclass classification tasks, nevertheless. We now take into account the cross-entropy function. The difference between two probability distributions can be represented by the Kullback-Leibler divergence (KLD), whose expression is stated as follows:

$$D_{KL}(T||R)= \sum_j \mathrm{P(i)} log\frac{T(i)}{R(i)}(x) \quad (15)$$

$$H(P,Q)=D_{KL}(T||R)+H(P) \quad (16)$$

Simulation and Analysis

The numerical results for various parameters are presented as we construct the deep learning-based NOMA signal detection system we looked at how the proposed plan performed in comparison to the conventional SIC method in a particular situation. Then, the performance of the symbol error rate (SER) was investigated in relation to a variety of MIMO-NOMA modulations. The impact of the power allocation factor on system performance was then simulated.
The situation in which the actual CSI differs from the estimated one was then examined. Additionally, we carried out simulations with a variety of mini-batch sizes in order to speed up the MIMO-NOMA-DL algorithm's convergence. Finally, helpful suggestions for speeding up training are provided.

Machine learning can be done with MATLAB, with packages, were utilized in our numerical analysis due to their effectiveness and ease of use. We concentrated on a single cluster with two UEs for simplicity's sake. A complex Rayleigh distribution and a four-by-four MIMO channel were considered. Let an antenna received 1W of transmitted power, with UE1 receiving 8/10 and UE2 receiving 2/10
By evaluating the proposed MIMO-NOMA-DL signal detection with the current MIMO-NOMA-SIC approach, the performance gap was assessed. The modulation type of both UE superposition coding signals at the transmitter was supposed to be binary phase shift keying, and the SIC's knowledge of channel characteristics was flawless (BPSK). The UE1 signal, which views the UE2 signal as interference, should be demodulated first in the conventional MIMO-NOMA-SIC detection system. After the modulated UE1 signal has been eliminated

from the received NOMA-MIMO transmission, we may then demodulate the UE2 signal. However, in the MIMO-NOMA-DL approach, the received signal is passed to the DNN, and during the training phase, labels are only selected for the UE2 sequence. The numerical simulation's SER-SNR curve is displayed in Fig. 9.

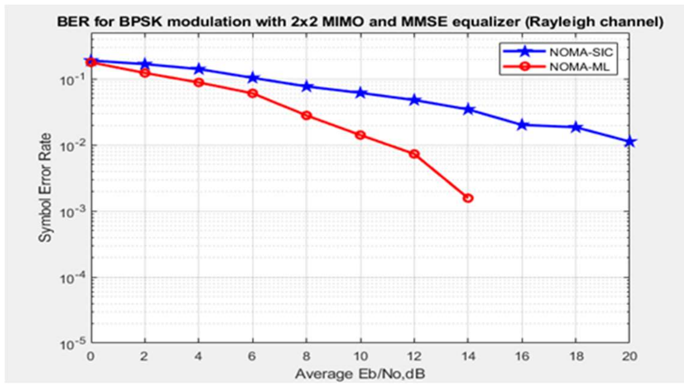

Fig.9. Comparison of Performances of MIMO-NOMA-ML and MIMO-NOMA-SIC

The detection performance in these three scenarios is shown in Fig. 10. It is obvious that the MIMO-NOMA signal detection based on the DL system performed well. In addition to the previously mentioned instance 1, case 2 and case 3 both saw performance gains of around 3.5 and 1 dB, respectively. These findings suggest that the DNN may be used to learn both the characteristics of the wireless MIMO channel with Rayleigh fading and the signal demodulation with NOMA.

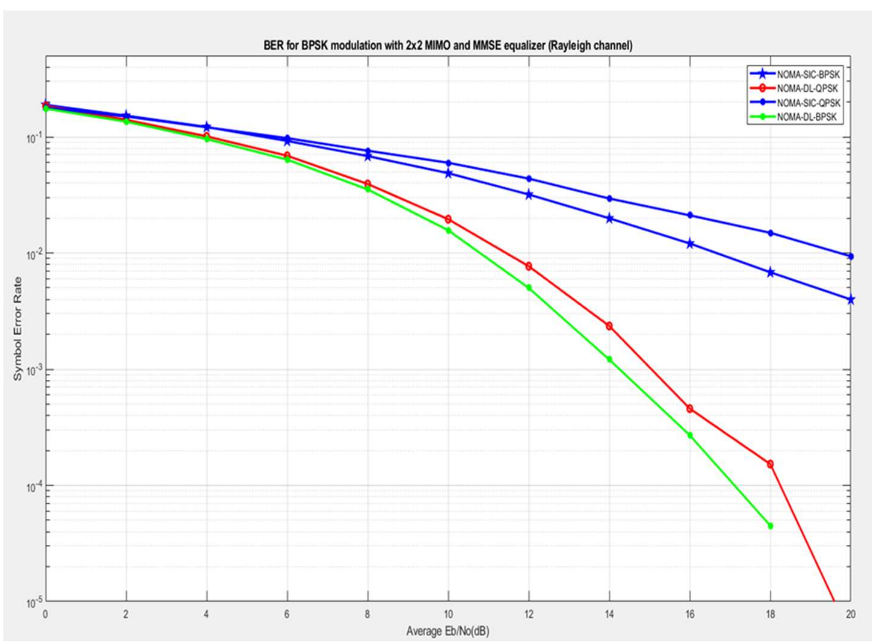

Fig.10.Comparison of Performances of MIMO-NOMA-ML and MIMO-NOMA-SIC

Conclusion

The performance of the MIMO NOMA system has been improved by using Deep learning Technique compared to Successive Interference Cancellation Technique as we can observe that Bit Error rate has been reduced in the above analysis. By comparing performances of MIMO-NOMA using various QPSK and BPSK Techniques in both SIC and Deep learning methods we found that MIMO-NOMA DL using BPSK is a productive version and can be implemented in 5G networking systems

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