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Original Paper

DEEP LEARNING BASED SIGNAL DETECTION AND CHANNEL ESTIMATION FOR MIMO-NOMA SYSTEM

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ABSTRACT

The increasing demands for enormous connectivity, low latency and high reliability of future communication networks require new techniques. Multiple-input-multiple-output and non-orthogonal multiple access (MIMO-NOMA), which contain the NOMA concept into MIMO, is an appealing technology to reinforce system capacity and spectral efficiency in the future communication scenarios. However, rapidly changing channel conditions and high computational complexity because of SIC degrade system performance. Thus, to tackle these limitations, in this paper, we propose a deep learning based MIMO-NOMA framework for data detection and estimate sharply changing channel conditions. To be specific, we design an effective deep neural network for communication in which several convolutional layers and multiple hidden layers are included. The NOMA-MIMO-DL framework addresses the data detection problem for achieving a lower signal error rate and detect the channel characteristics automatically of MIMO-NOMA. In general, we build, train and test the proposed cooperative framework to appreciate automatic encoding, decoding, and channel detection in a relay feeding channel. Simulation results demonstrate that the proposed scheme is robust and efficient compared to standard approaches.

KEYWORDS

Deep Learning, NOMA-MIMO, Signal Detection, Channel Estimation

1. INTRODUCTION

Non-Orthogonal multiple access (NOMA) has been considered as an optimum technique to enhance spectrum efficiency for the 5th generation (5G) networks has captured great interest within both academia and industry [1]. Different from traditional orthogonal multiple access (OMA), NOMA is capable of serving multiple users using the same time and frequency by the same base station (BS). In NOMA, the information signals are combined using superposition coding in the same frequency at different power levels and adopt successive interference cancellation (SIC) to detect signal [2]. By designing SIC means subtract high power from the weakest user then re-modulate and re-transmit to the user having a low power signal at the receiver. At each user, to schedule the transmission of signals over the same transmission period and bandwidth, superposition coding (SPC) is used 2015 [3].

In [4], the performance of the NOMA investigated in a cellular downlink scenario with randomly deployed users. to improve the ergodic capacity of each user, a Fair-NOMA approach was applied in the case of pairing a near BS user and a cell-edge user [5]. Most recently, to meet the 5G goal of explosive data traffic growth soon resulting from massively connected equipment, a different perspective has been developed as a solution [6], [7]. Additionally, multiple-input-multiple-output (MIMO) is a method of multiplying the capacity of a radio link using multiple transmission and receiving antennas. By simply deploying additional antennas, MIMO can exploit multipath propagation [8]. The combination of the MIMO technique to NOMA can address challenges like massive connectivity, low latency, and high reliability gives additional degrees of freedom to the system for further performance enhancement [9], [10]. Also, MIMO-NOMA is a better combination to improve spectral efficiency and reduce the latency of communication networks.

Inspired by the promising performance, various schemes have been proposed for MIMO-NOMA based systems. In [9], a new technique with the high spectrum and energy efficiency, namely, the millimeter-wave transmission that incorporates the concept of NOMA into beam space MIMO proposed to boost the energy and spectrum efficiency. Then, user clustering proposed for a mm-wave-NOMA scheme in [10], NOMA is implemented for users in the same cluster and MIMO detection is employed to remove inter-cluster interference. However, in [10], spatial degrees of freedom cannot be obtained at the BS, which strongly degrades the power efficiency and detection performance. To addressing a problem, an opportunistic matrix precoding method was proposed for the non-separable wireless MIMO-NOMA frameworks [11]. Besides, by designing a novel MIMO-NOMA transmission strategy for users in the same group, which outperforms both OMA transmission and signal alignment NOMA system in terms of the total power consumption [12]. MIMO-NOMA theoretically demonstrated to provide a higher capacity and sum-rate than the MIMO-OMA systems in 4th generation, and power allocation strategies investigated in many pioneering works. In [13], the author proposed to group the receive antennas at the users into many clusters dynamically and derived power allocation solutions to maximize the overall cell capacity, where the number of clusters is no less than that of the transmit antennas at the BS.

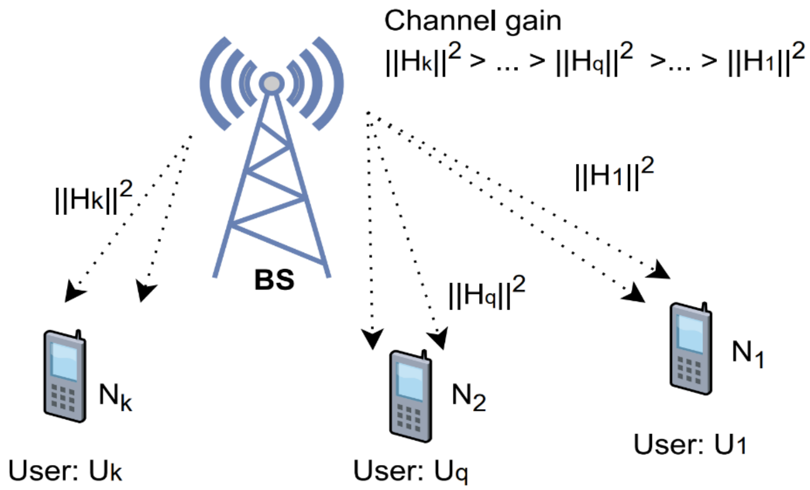

Figure. 1 - block diagram of MIMO-NOMA. Base Station(BS)

Practically, channel state information (CSI) has a significant impact on the performance of the MIMO-NOMA system and a lot of works devoted to realizing channel estimation based on the MIMO-NOMA scenarios. SIC requires the perfect CSI at each user, and the potential gain of the system depends mostly on the accuracy of CSI. Also, the decoding error of the high-power signal affects the decoding accuracy of the low-power signal, that is the key problem of SIC. However, due to the high complexity and computation, it is quite difficult to acquire accurate CSI in MIMO-NOMA systems which is to be implemented in low power device.

As a result, the performance of the MIMO-NOMA schemes degraded because of SIC. Previously proposed methods are only capable of deriving the sub-optimal solutions, thus the conventional method is imperfect to achieve better performance of the existing communication systems and practical implications of MIMO-NOMA is limited. Hence, an efficient way to acquire perfect CSI and remove SIC based methods is a major issue in the MIMO-NOMA where new methods should explore to resolve this problem.

Motivated by the above considerations, new theories should be explored to enhance the performance of MIMO-NOMA systems in low power devices. Recently, the deep learning(DL) technique [14], which is a branch of machine learning(ML), has been widely demonstrated to be a data-driven tool to deal with big data and resolve nonlinear problems. Though DL-based wireless communication is not a much-matured field, some pioneering works conducted and its superior performance has been initially verified [15], [16], [17], [18], [19], [20]. Also, deep learning in wireless communication has been roughly investigated for channel coding, millimeter wave (mmWave), the cognitive radio, unmanned aerial vehicles, OFDM receivers, and offloading framework for mobile users [21], [22], [23]. In [15], the authors first incorporated deep learning into NOMA and the excellent performance of such Long Short-Term Memory(LSTM) Network-based NOMA system demonstrated in terms of encoding, decoding, and channel detection. In [15], LSTM based model training requires a lot of resources and time for computations to get trained and get ready for real-world applications. Meanwhile, Convolutional Neural Network(CNN) is computationally efficient and designed to exploit “spatial correlation” in data and works well on images and speech data. In [16] deep learning was introduced for MIMO-NOMA downlink signal detection using dense neural network(DNN) but rapidly changing channel condition make difficult to extract perfect CSI in DNN based MIMO-NOMA systems. Thus, it is of great significance to apply a convolutional neural network(CNN) based model in MIMO-NOMA systems for optimizing the system in an end-to-end manner.

Traditionally, the SIC method affected by the error propagation (EP) and receiver complexity increase to the number of users. We propose a DL-MIMO-NOMA framework based on CNN and deep learning method to estimate the channel and decode the original signal.

To optimize the model for signal detection and channel estimation of the MIMO-NOMA system which shown in Fig. 1, this work carries out comprehensive research and provides a deep learning-based framework. In Brief, the main contributions of this paper listed as follows. To the best of our knowledge,

- This work attempts to merge state-of-the-art deep learning with MIMO-NOMA systems. Use deep learning methods instead of traditional successive interference cancellation to detect a signal. The proposed deep learning-based framework is also able to estimate an unknown channel environment.
- We construct a novel deep neural network for communication to approximate the MIMO-NOMA system, in which multiple carefully-designed hidden layers and convolutional (Conv) layers are processed by specific activation functions. Also, based on the proposed framework, a novel signal detection method is provided for improving bit error rate (BER) compare to DNN based model [16].
- Extensive performance analyses presented for evaluating the performance of the proposed NOMA-MIMO-DL framework in terms of the BER and shown that the proposed framework outperforms other existing schemes, which fully proves the effectiveness of the deep learning-based MIMO-NOMA system.

The remainder of paper as this. In Section II, we construct a typical NOMA system with multiple users and antennas. Then, a System model that incorporates CNN into the MIMO-NOMA system proposed in Section III, we formulate the signal detection and channel estimation problem. Proposed DL-MIMO-NOMA framework to solve this prohibitively high complexity issue. The Simulation results used to evaluate the performance of the proposed schemes provided in Section IV and conclusions in Section V.

Notations: Vectors are denoted by italics small letters, while matrices are defined by capital letters; $(\cdot)^*$, $\|\cdot\|$ superscripts, the Frobenius norm operator respectively. Also, C (N × M) is denoted as the vector space of all $m \times n$ complex matrices.

2. SYSTEM MODEL

We consider a typical downlink MIMO-NOMA system with one BS with a uniform linear array (ULA) [24] of M antennas and D multi-antenna users, where the Rayleigh fading scenario assumed in the downlink channel. Here, each user equipped with N antennas and we assume that the BS has no information on each link of the user. To avoid the complex and impractical beamforming vector allocation issue [25], this paper supposes that $N \geq M$ [10]. As reported in [6], [10] small cells implemented in 5G wireless networks ultra-densely, where the number of low-power and low-cost small-cell BSs can be massive. Thus, it is reasonable to assume that such a low-power BS is equipped with the same or even a smaller number of antennas compare to the user equipment (UEs). Noting that the $M \times 1$ source vector as s, supposing that the number of users is K, the received signal at the kth user is given by,

$$Y_k = H_k x_i + Z_k = \sum_{i=1}^{k} H_i * \sqrt{a_i \square P s_i} + Z_k$$

Where s the information-bearing signal. the ith user signal at the BS can be denoted as x_i, where $i = 1, 2, \cdots, K$. The power allocated to ith user is denoted as a_i, and the transmission power is limited by the total power P, where $P = a_1 + a_2 + \cdots + a_k$. z is Gaussian noise aided at receiver. we assume the power allocation coefficients are ordered as $p_1 > p_2 > \cdots > p_k$. Then, $H_{m,k} \epsilon\, C\, (N \times M)$ represents the channel matrix including the distance-dependent path loss effect for the kth user. As mentioned previously, at the receiver, the SIC process is executed in descending order of signal-to-noise ratio (SNR) Hence, a user with the bad channel will decode directly while the other signals viewed as noise. Hence, q as the user index and $1 < q \leq K$, the SINR for decoding the qth user's signal, achieved at the qth user is

$$\gamma^q = \frac{a_q \, ||H_q||^2}{\sum_{i=q+1}^{q} a_i \, ||H_q||^2 + 1}$$

For a user, $k \epsilon [1, K]$, assuming that the firstk-1 users decoded perfectly, the throughput for kth user is

$$\gamma^k = a_k \, ||H_k||^2$$

The decoding error of the higher-power signal is accumulated and affects the decoding accuracy of the low-power signal. That is the main problem of the SIC method that must be solved. Afterwards, through designing the estimation and detection techniques appropriately, we exploit deep learning aided MIMO-NOMA framework.

3. DEEP LEARNING BASED MIMO NOMA

In this section, inspired by state-of-the-art deep learning, we merge the deep neural network with the MIMO-NOMA system and derive an end-to-end approach for signal detection and channel estimation. To boost the end-to-end performance, DL-NOMA-MIMO view as auto-encoder, in which encoder estimates channel and decoder decode original information from the received signal. To improve system performance, an effective learning method provided to train the DL-MIMO-NOMA. Furthermore, based on the DL based framework, superior algorithms are proposed for improving the MIMO-NOMA system.

3.1. Problem Formulation

For the MIMO-NOMA system, we aim to improve the error rate performance. Instead of SIC, we use detection network to extract original information s from received signal Y. Thus, after developing a detection network based on CNN to detect signal, DL-MIMO-NOMA employed to learn the channel characteristics of NOMA systems. Performance of DL-MIMO-NOMA based end-to-end communication system simulated via training and testing algorithm.

Deep learning, which is theoretically demonstrated an appealing tool to approximate complicated problems. By implementing a DL-MIMO-NOMA framework with sufficient neurons and hidden layers can optimize the above problem.

3.2. Proposed DL-MIMO-NOMA Model

In this section, we design a DL-MIMO-NOMA framework which is a deep neural network with convolutional layers and fully connected layers followed by dense neural network for optimizing the MIMO-NOMA system. Over the past several years, deep learning has been widely used in various emerging fields, such as computer vision, natural language processing, automation, etc. As reported in the well-known *universal approximation theorem* [26], a feed-forward network with a single hidden layer facilitated by multilayer perceptron technique is capable of approximating continuous functions on compact subsets of R^n. Since the statistics of the MIMO-NOMA system can be extracted by information propagation in multiple hidden layers, the NN is capable of resolving large quantities of non-convex and non-linear functions. It noted that MIMO-NOMA systems require complex channel estimation to perform SIC, and the proposed powerful DL-MIMO-NOMA model is a good candidate to overcome these challenges.

Our proposed DL-MIMO-NOMA framework considers the MIMO-NOMA system optimization problem as an exhaustive search problem. It extracts the features and correlation of the samples (i.e., channel vectors, power allocation factors, transmit power, and noise) and traverses all the policies by non-linear mapping. With the aid of the effective learning mechanism, the DL-MIMO-NOMA framework can search for the best parameters through backpropagation. Also, convolutional layers used to design the DL-MIMO-NOMA framework is very likely to approximate the optimal solution without requiring high computational complexity.

Before developing the proposed DL-MIMO-NOMA framework, in brief, the deep neural network is an extension of traditional artificial neural networks [27], in which multiple hidden layers with a large number of neurons designed. The input data travel from the first (input) layer of the DNN to the last (output) layer possibly after traversing the layers multiple times. For the

$$Out = f\left(x_{in}; w\right) = f^{(n-1)}\left(f^{(n-2)}\left(\cdots f^{1}\left(x_{in}\right)\right)\right)$$

activation functions of the particular layer, the Sigmoid and Rectified Linear Unit (ReLU) functions are the most commonly used as an activation function for NN. we can write
where n and w defined as the number of layers in DNN and the weights of the network, respectively. Out and x_{in} to be the output and the input.

Now, we develop a novel detection network based on the proposed MIMO-NOMA system. Initially, the input of a detection network is Y. First, for 8 × 8 MIMO-NOMA system the received signal is 16 bit because of a complex number in a channel. Then 16 bit of that signal converted into 1 × 4 × 4 shape as input layer of detection network. then, the first layer designed as a convolutional (Conv) layer with four 2 × 2 filter, one zero paddings, and one stride to generate feature maps, following the ReLU, then the following layer is designed as a max-pooling layer with 2 × 2 to down-sample the input data and reduce the dimensionality. Here, we use the Maxpooling method to achieve pooling operation, which employs a max filter to realize the non-overlapping division of the input and calculate the maximum of these subregions. Specifically, this layer comprises one channel. The concept of “channel” is different from the “wireless channel” it represents the number of feature maps to the neural network (i.e., if the number of channels is c, then the number of inputs (i.e., the number of feature maps) should be c). The first channel consists of the real and imaginary parts of the received signal.

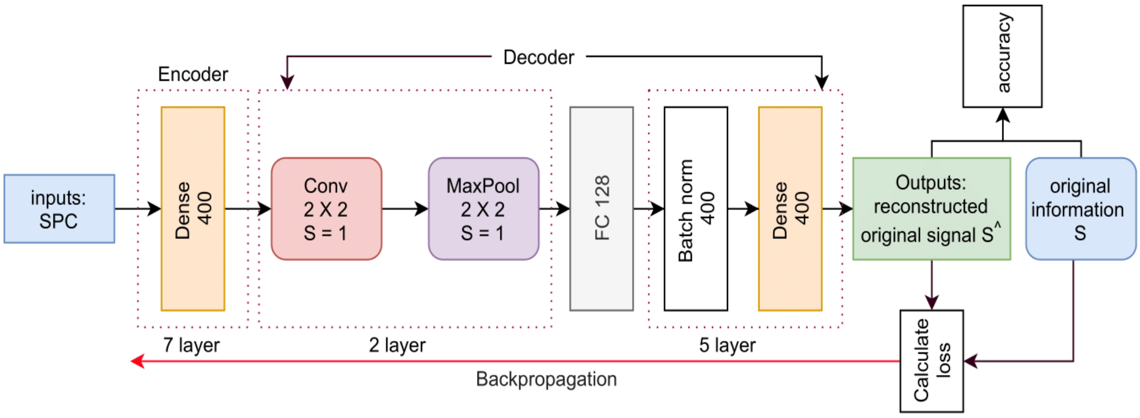

Figure. 2 - A Deep Learning based MIMO-NOMA framework for end-to-end communication system model design to detect signal and estimate channel.

In the MIMO-NOMA system, the training samples with spatial information are in multiple dimensions so they can regard as images and the Conv layer is a state-of-the-art candidate to extract such multi-dimensional features mapping. This progress is benefited from the fact that parameters sharing and local connectivity mechanisms have been used in the Conv layers. The first Conv layer propagates the useful characteristics (e.g., the channel matrix Hm, noise) of the input signals to another Conv layer with eight 2 × 2 filter followed by ReLU and Max Pooling. Then, the Conv layer propagates the useful characteristics of the input signals to the fully connected(FC) layer with 128 neurons, in which 128 represents the maximum classes of features that can be mapped in a network. Following the Conv layers, an FC layer designed as a noise layer that can adapt the noise and the distortion level according to the given scenarios. In this case, the FC layer makes the network fit the changes in the environments. then five dense layers to implemented, each employing 400 neurons and these layers adopt batch-normalization with Relu activation function. The ReLU function achieves excellent performance in nonlinear operation, and it can hinder the gradient exploding and gradient vanishing problems.

After developing a detection network we develop our DL-NOMA-MIMO framework for end-to-end communication. In which we add 7 dense hidden layers of 400 neurons followed by a detection network. In that input, Signal is super position-coding X mapping to y. The detection network extracts original information by minimizing a bit error rate. Here, based on the developed DL-NOMA-MIMO, we approximate detection and estimation problem as a continuous function through the powerful deep-learning technique and find the optimized solution.

3.3 Samples Generation

As a DL-enabled framework, abundant sample collection is a key issue for training the DL-MIMO-NOMA. Here, in each simulation, various transmit data sequences and channel vectors are obtained in different channel environments, such as Additive white Gaussian noise(AWGN), flat fading, and frequency selective fading environments, etc. To be specific, it is first trained based on a Rayleigh fading channel and the well-trained model regarded as a basic model M_0, and then M_0 can be trained in another channel by using transfer learning method [28]. This procedure is called feature-based transfer learning, which compares the similarities in the samples between the Rayleigh channel and the new channel such as the AWGN channel. The features remain the same if the features are similar, or new features are added to the basic model M_0 by conducting training the samples from another channel. If its performance is degraded in the AWGN channel, the model needs to be tuned until it performs well in both the Rayleigh and other channels.

We obtain the corresponding received signal vector y_k based on the given fixed channel model according to equation. Concretely, once a transmitted sample sent into the channel, we can collect the received vector y_k in a specific direction under a special power constraint. Hence, we obtain samples under various values of Signal-to-noise ratio(SNR) and then we can obtain the corresponding channel vectors $\| H \|$. Also, we generate data according to different power allocation coefficients P_i in the region of [0, 1] randomly and these data adopted as part of the training samples. In the context, to achieve generalization of the model for detection and estimation of the MIMO-NOMA, we obtain samples of different training data based on different values of SNR and different channel matrices that generated randomly. Each group of Data samples aligned to specific channel conditions and SNR and sufficient samples are obtained for training the DL-MIMO-NOMA framework. Then, by setting sampling intervals of the SNR, this process repeats until global traversal completed. In this way, the samples for the DL-MIMO-NOMA framework obtained.

In our experiments, to initialize the parameters of the model by simply randomly initialize the parameters. However, in some scenarios, random initialization may lead to some infeasible solutions at times. Hence, the proposed scheme integrates the knowledge into the network before training, which serves as a good initialization for enhancing system performance. This is essential for avoiding infeasible solutions during the learning process since a good initialization can modify the optimization paths. After initialization, the DL-MIMO-NOMA can conduct online or offline training with low complexity as indicated in other parts of this work. Therefore, we can realize low-complexity offline or online training in extensive scenarios with the aid of the DL-MIMO-NOMA, since the learning procedure does not include the initialization method that only requires for the first time.

3.4. Learning Mechanism

Effective learning policy has a great impact on the performance of a DL-based framework. To boost the DL-MIMO-NOMA framework, we propose a novel training mechanism and realize the end-to-end performance of the MIMO-NOMA. The input of the detection network is the received signal of y_k. Meanwhile, $\tilde{a}_1$, $\tilde{a}_2$, $\cdots$ $\tilde{a}_m$ is the network output, which are the original input signal predicted by network.

Algorithm 1 DL-MIMO-NOMA based training algorithm

Input: Environment simulator, DL-MIMO-NOMA model
Output: DL-MIMO-NOMA model
1: Initialize the DL-MIMO-NOMA framework.Set the key parameters, including number of antenna, batch size, iterations, SNR range, mini-batch, learning rate, and initialize the parameters of each layer, etc..
2: Generate a set of data sequences from the training data set of each user
3: Start the environment simulator to generate the wireless channel, and mix specific man-made noise or distortion into the channel based on SNR.
4: Implement the forward process and obtain the results of the output layer's data denoted as $\{\widehat{s_1}, \widehat{s_2} \cdots, \widehat{s_m}\}$
5: Calculate the loss function, that is, the cross-entropy

$$Loss(s, \widehat{s}) = \sum_{m} s_i log \frac{s_i}{\widehat{s_i}} + \lambda \cdot \sum^{m} \|w_i\|_2 \tag{6}$$

6: Calculate the corrective parameter with the SGD optimization algorithm. Update the parameters with the algorithm to search for the optimal solution
7: **return:** DL-MIMO-NOMA model

Now, we train the DL-MIMO-NOMA framework with given samples where input is SPC signal X. After training the DL-MIMO-NOMA framework with all the samples, we complete the offline learning procedure and obtain the well-trained DL-MIMO-NOMA. Then, to adapt to new-exposed samples and scenarios, we conduct an online learning policy for attaining the optimal BER. Online learning can be regarded as a specific branch of active learning. In other words, it can conduct additional training when it is in service. Furthermore, it's noted that essential to derive an appropriate loss function to optimize the DL-MIMO-NOMA framework. The loss function of DL-MIMO-NOMA is cross-entropy loss function. To be specific, as a deep learning-based scheme, this approach is divided into a training algorithm and testing algorithm, which is present in Algorithm 1 and Algorithm 2.

Algorithm 2 DL-MIMO-NOMA based testing algorithm

Input: $X = \{x_1, x_2 \cdots, x_m\}$ Super Position Coding(SPC) Signal for all users, environment simulator.
Output: Reconstructed information signal: $\{\widehat{s}_1, \widehat{s}_2 \cdots, \widehat{s}_m\}$

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Load the DL-MIMO-NOMA network.
Start the environment simulator to generate the wireless channel, and mix specific man-made noise or distortion into
  the channel based on SNR.
Process the DL-MIMO-NOMA network.
Update the output of the DL-MIMO-NOMA network.
Transform S estimated signal vectors into absolute values. then, calculate SER to measure performance.
return: ŝ^[m] = s^[m], m = 1, 2 ⋯, M
```

Additionally, for regularization of a model, we add a dropout layer to prevent the infeasible outputs of the DL-MIMO-NOMA and generalize well to be better at predicting. Afterwards, the stochastic gradient descent (SGD) algorithm is introduced to optimize the proposed DL-MIMO-NOMA framework and design accuracy function to measure the performance.

4. Simulation Results And Analysis

In this section, we discuss a numerical analysis of our proposed DL-MIMO-NOMA scheme with different parameters. We investigate the symbol error rate for the various value of SNR by changing a number of an antenna in MIMO, and the performance on different hyper parameters of the model discussed to evaluate the performance of the proposed system model. Also, to investigate the proposed DL-based detection approach, an extensive simulation is conducted. In our work, binary phase-shift keying (BPSK) modulation used in a system. please noted that the samples are generated randomly with Gaussian distribution. Additionally, the Rayleigh fading the channel deployed as a wireless channel.

Many software and tools are available for deep learning. Python 3.8 used in our performance analysis. To establish the DL framework and process the training procedure, the powerful open-source DL-framework from Facebook, PyTorch is employed to train the proposed system. we conduct our entire research in the cloud, google colab which provide GPU and rich coding environment for ML. To achieve faster training without loss of generality, the total randomly sampled mini-batch is treated as a “big training example”, the operation of the proposed approach based on the averaged values of all training samples in the mini-batch. In our simulation, a single cluster with two users MIMO-NOMA System taken into account, where BS is located at the centre and users are distributed randomly. information signal generated randomly, which transmitted via BPSK modulation. Power allocation factor is 0.8 for bad channel user and 0.2 for good channel user. Total transmitted power is the average of squared SPC signal x. Then, noise power σ, which is noise added in the system as per SNR and value of transmitted power. Learning rate and batch size set as 0.01 and 5 in simulation. Also, the training data set is consisted of 2500 samples in the simulation, whereas a test set includes 500 samples.

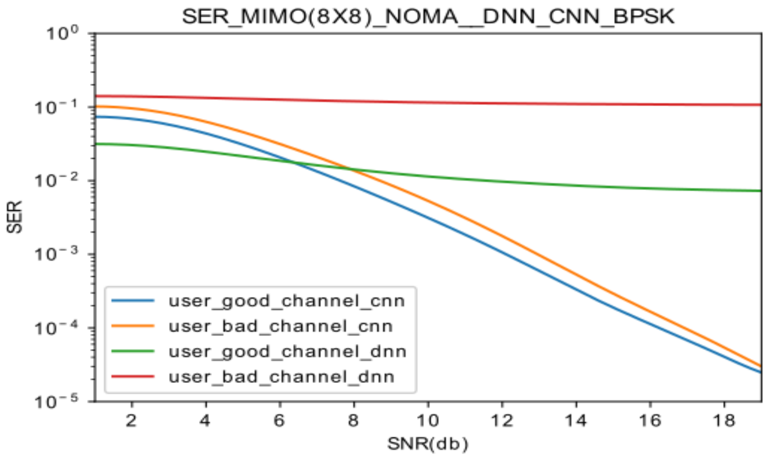

Figure 3: SER Vs SNR for different MIMO (8 × 8) - NOMA based communication system

Fig. 3 shows the results in terms of the SER of the NOMA system for each user with channel condition. It can be seen from Fig. 3 that the user with good channel condition performs better compared to the user having a bad channel because signal distortion is high for bad channels. Additionally, with the enhancement of the SNR, SER deteriorates simultaneously.

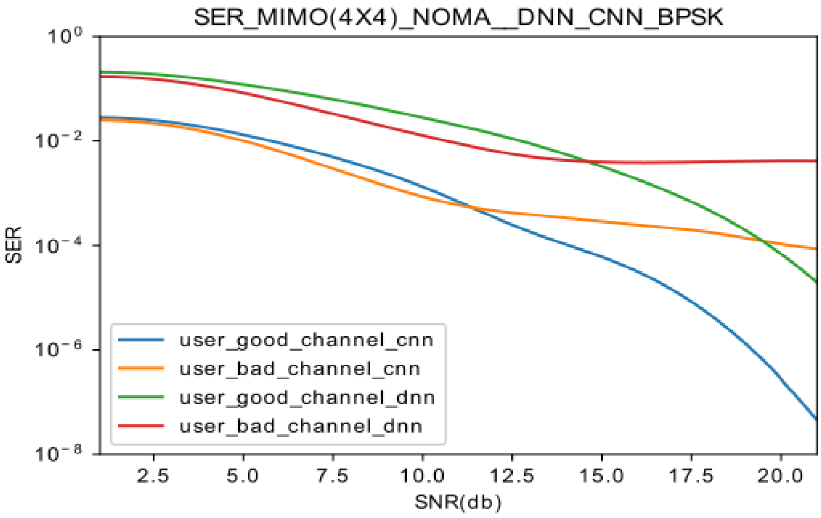

Figure 4: SER Vs SNR for different MIMO (4 × 4) - NOMA System.

In this simulation, we investigate the results in terms of the SER vs SNR for 8 × 8 MIMO, 4×4 MIMO, 2×2 MIMO-NOMA scheme. As can be observed from Fig. 3, 4 and 5 the proposed DL-MIMO-NOMA scheme outperforms the DNN schemes [16] in terms of the SER. Here, the sequence length is set as per the number of input antennas in MIMO for a fair comparison between different schemes. the performance of the proposed DL-NOMA-MIMO framework improves with increasing SNR, SER goes below 10^{-6} for 25 dB SNR. The plots indicate that the encoders and decoders have learned the channel characteristics without any prior knowledge regarding the NOMA system, obtain current and accurate CSI as well as to detect original information signal from received signal at a receiver.

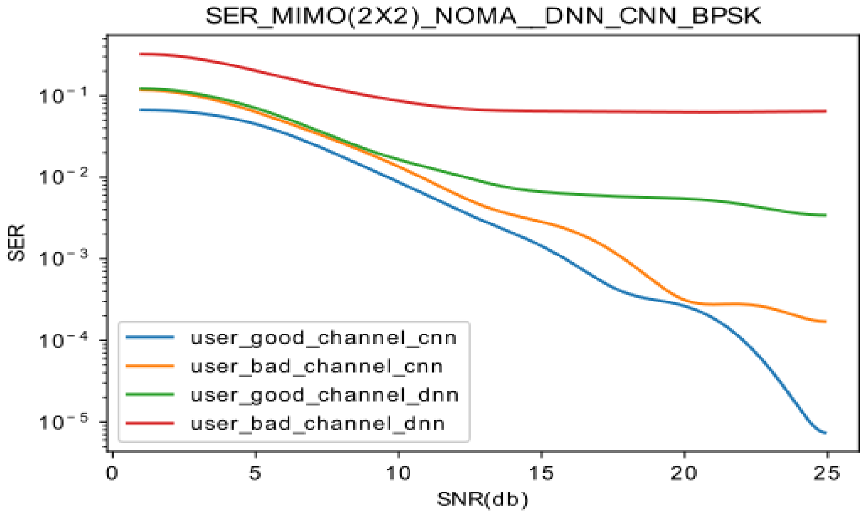

Figure 5: SER Vs SNR for different MIMO (2 × 2) - NOMA system

Make communication robust in the link between BS and each user. Thus, the DL based model works for an end-to-end scenario where model estimates channel and detect signal for MIMO-NOMA. Thus, CDNN framework, which is a DL based method to allocate power coefficient in MIMO-NOMA System merge with our proposed DL-MIMO-NOMA model, to optimize MIMO-NOMA system in an end-to-end manner.

Paper [16] designed DNN based MIMO-NOMA signal-detection system to perform signal recovery. Compare that model with our CNN based DL-NOMA-MIMO framework. CNN based model works better while DNN performs plateau as SNR increase because CNN based model, estimates channel well at training time having superior ability to represent complex channel. user which is far from bs has high SER because of complex channel environment. So, as increases channel complexity makes it difficult to recover the original signal

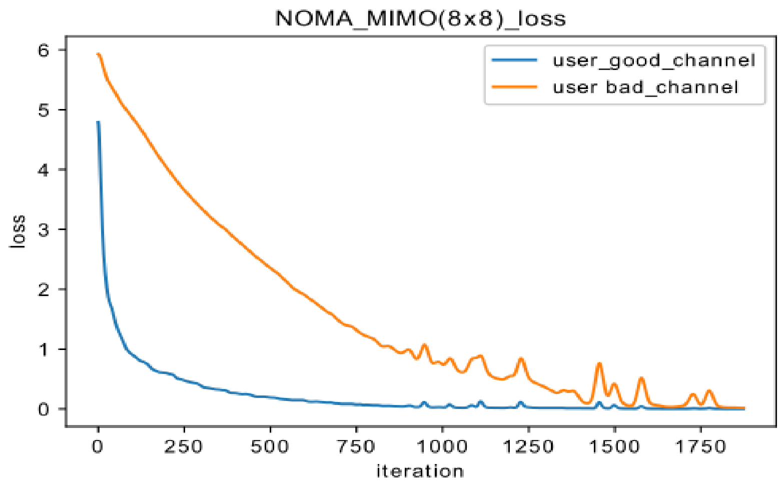

Figure 6: loss Vs training epochs for user with good and bad channel condition

In Figure 6, 7, we study the relationship between the accuracy, loss with respect to the training epochs at training iterations. As the number of epoch increases, the loss decreases and accuracy increases initially and then finally becoming stable. In particular, it can be observed from Fig. 6, 7 that the performance of the user with bad channel condition is lower than that of the good channel condition. Also, we can further see that the good channel user converges quickly compared with the bad channel, as its curve becomes smooth and initially remains unchanged. Hence, we come to an initial conclusion that user with good channel condition performs better even though we allocate a low power factor.

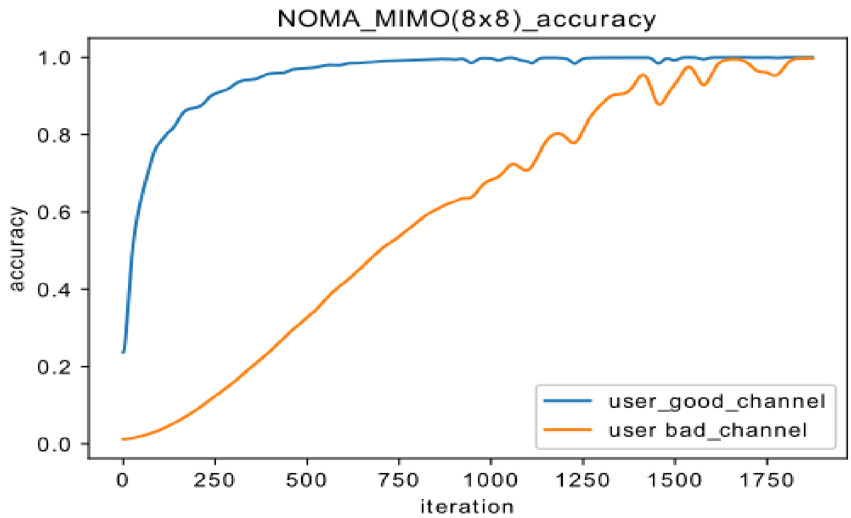

Figure 7: accuracy Vs training epochs for user with good and bad channel condition

In a deep learning-based communication system, as the number of antennas increases complexity increases and more computation require to converge the model. Also, the performance of the model proportional to the number of layers in the model, which require more computation power to train.

5. Conclusions

In this paper, by integrating deep learning into the MIMO-NOMA system, we have proposed a DL based scheme for optimizing the communication system. We designed a DL-NOMA-MIMO framework where a specific model developed for end-to-end communication. Then, novel learning methods provided to estimate the channel and detect the signal of the MIMO-NOMA system. The impressive representation and mapping capacities of the deep learning enable the MIMO-NOMA system to attain accurate CSI and achieve better BER performance at the users and the end-to-end optimization problem addressed with the aid of the approximation ability of the model. Furthermore, simulation results show the superior performance of the CNN-based MIMO-NOMA framework. In the future, this work can be extended to the time-varying fading channel scenarios, in which the model needs to follow the instantaneous fading conditions.

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