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MIMO-NOMA FOR SUCCESSIVE INTERFERENCE CANCELLATION IN 5G COMMUNICATION USING DEEP LEARNING APPROACH

[1]L.Lakshmi Prasanna Kumar,[2] K.E.Srinivasa Murthy, [3]M.N.Giri Prasad
[1]Research Scholar, Dept of ECE JNTUA,Anantapuramu, Andhra Pradesh, India
[1]Dept of ECE, G.P.R.E.C, Kurnool, Andhra Pradesh, India
[2]Dept of ECE, R.C.E.W, Kurnool, Andhra Pradesh, India
[3]Professor, Dept of ECE, JNTUA,Anantapuramu,. Andhra Pradesh, India
[1]lankekphd@gmail.com, [2]kesmurthy@rediffmail.com, [3]mahendragiri1960@gmail.com

Abstract: The paper presents a novel deep learning algorithm that can be used to cancel the interference caused by multi-input multiple-output system called MIMO-NOMA. The proposed method is designed to address the challenges of the traditional SIC schemes, such as the high computational complexity and error propagation. It utilizes a deep neural network to directly decodes the signals from each user to the corresponding data. The proposed scheme is performed through a simulation to evaluate its performance. It shows that it can perform better than the traditional approach when it comes to signal detection and channel estimation. The proposed algorithm performs better than the traditional SIC schemes in terms of its bit error rate. It also maintains low computational complexity.
Keywords: Deep learning, MIMO-NOMA, Successive interference cancellation, Bit error rate, Softmax.

1. Introduction

Deep learning (DL) is a promising tool for developing data-driven methods in the telecommunications industry. It can help develop new methods for analyzing and mapping the various features of the data collected in the physical layer [1]. It can also reduce the computational complexity of signal processing algorithms by replacing the existing ones [2]. DL can also be used to merge multiple processing blocks to create an end-to-end system. The rapid growth of data traffic and connectivity has made it important that the development of next generation wireless networks is expected to require the use of advanced technologies. DL can be used to replace the existing signal processing algorithms in a communications system [1]. It can also be used to merge multiple processing blocks to create an end-to-end system. The rapid growth of data traffic and connectivity has made it important that the development of next generation wireless networks is expected to require the use of advanced technologies.

Non-orthogonal multiple access has been shown to be a promising alternative to traditional multiple access for enhancing the efficiency of the spectrum [3]. The paper aims to study the power-domain NOMA of uplink multiple-input multiple output (MIMO) systems, such as the MIMO-NOMA. These systems involve sharing the same time-frequency resources, which can result in different power levels being transmitted [4]. The receiver side of the system uses a signal detection technique known as successive interference cancellation to identify the desired signals. This method involves performing signals decoding progressively in order to determine the strengths of the users [3]. SIC works by subtracting the signal from the combined signal of the strongest user and the next user before determining which one should be decoded. Each user then treats the other interfering ones.

A variety of schemes have been developed for making use of the features of the combined signal in a MIMO-NOMA system. These include having the perfect knowledge of the channel state information (CSI), signal decoding, and perfect cancellation [4-7]. In principle, SIC can be performed in a multi-channel system, but there are various constraints that prevent it from being fully utilized in such a system [8]. One of these is the high complexity of the computation and the error propagation caused by channel estimation errors. This paper aims to address these issues by developing a DL-based approach. Several studies have been conducted on the applications of DL in NOMA systems.

In particular, the authors [9] proposed a DL approach to detect downlink signals in the SIC receiver. The proposed method involved replacing the entire receiver with a deep neural network. The output layer of the DL system is composed of groups that represent the various transmit antennas. The goal of the system is to identify the corresponding downlink signal. The performance of the proposed system was studied due to the various factors that affect its performance. However, the authors found the proposed method to be very inaccurate when it comes to analyzing the channel parameters.

In this paper [10], a DL approach is presented that combines the advantages of a precoder and an SIC decoder in a downlink MIMO-NOMA system. The two components are designed to minimize the mean squared error between the received and decoded signals. Two SIC decoders are used at every step of the SIC process. The first one reconstructs the previous signal's transmit signal while the second one decodes the current user's signal. Only one SIC decoder is used at the first step of the process. Despite its advantages, the proposed scheme suffers from the high computational complexity. There are other DL-based NOMA schemes that can be used for the same purpose [11-12]. In the previous paper [12], the authors proposed a short-term memory network as a receiver scheme that can automatically detect the channel characteristics. They then used a sliding window detection method to speed up the NOMA process.

In this paper, we proposed a method that enables a base station to detect multiple users' signals in a multi-user uplink MIMO-NOMA scenario using deep learning. The method is very simple and does not require the user to explicitly cancel out the decoded signal. The proposed method utilizes a single Deep Learning model for each user. The output of the model is the decoded signal of that user. The input of the model is the combined signal of all the users' previous signals and the first decoded user. The proposed technique is more efficient and has better computational complexity than other DL-based methods.

The rest of the paper is organized as follows: Section 2 deals with the system model of the uplink MIMO-MOMA. Section 3 deals with the DL based SIC framework. Section 4 deals with the simulation results and finally conclusion is drawn in section 5.

2. System model

Figure 1 shows the single cell uplink MIMO-NOMA system, the uplink transmission in the form of an M-antenna BS is performed by K single antenna users. All of them share the same frequency band, and each user sends multiple frames to the BS. The superscripts D and P refer to data and pilot, respectively. The interval between frames is comparable to the coherence time, which is the time it takes to establish a fixed channel. During data transmission, the signal from all users received at the BS is given as

$$Y_0^D = H \Lambda X^D + V^D,$$

where $Y_0^D \in C^{M \times N}$ and the subscript 0 denotes the initial received signal before any SIC steps. $H = [h_1 ..., h_k] \in C^{M \times K}$ is the channel matrix between the BS and all the K users, where $h_k = [h_{k,1} ..., h_{k,M}] \in C^{M \times 1}$ denotes the channel coefficients between the BS and user k assuming Rayleigh fading.

Λ is a diagonal matrix defined by $\Lambda = diag\{\sqrt{\lambda_1},..., \sqrt{\lambda_k}\},$ where λ_k denotes the allocated power for user k. Let P_{max} represents the maximum total power consumption of all the uplink users such that $\sum_{k=1}^{K} \lambda_k \le P_{max}$. $X^D = [X_1^D,..., X_k^D]^T \in C^{K \times N}$ denotes the data matrix, where $X_k^D = [X_{k,1}^D,..., X_{k,N}^D]^T \in C^{N \times 1}$ is the vector of normalized modulated symbols of user k for data transmission within a single frame, i.e. $E\{|x_{k,n}^D|^2\} = 1, \forall n \in \{1,..., N\}$ and $\forall k \in \{1,..., K\}$.

$V^D \in CN(0, N_0 I_M)$ is the AWGN at the BS for data transmission. Similarly, the received signal during pilot transmission is given by

$$Y_0^P = H \Lambda X^P + V^P$$

where $Y_0^P \in C^{M \times L}$, $X^P = [X_1^P,..., X_k^P]^T \in C^{K \times L}$ denotes the pilot matrix and $V^P \in C^{M \times L}$ is the AWGN at the BS for pilot transmission. It was shown in [14] that it is not necessarily to allocate more power to users with poor channel. Accordingly, in this setup, we adopted equal power allocation such that $\lambda_k = P_{max} / K, \forall k \in \{1,..., K\}$ [7]. Let us assume the channel coefficients to be independent and identically distributed over all the antennas of the BS and the users. Without loss of generality, let us index the users in a descending order of their channel gains at the BS. That is, if a user has a higher channel gain, the user has a lower index, i.e., $\| h_1 \| \ge \| h_2 \| \ge ... \ge \| h_k \|$.

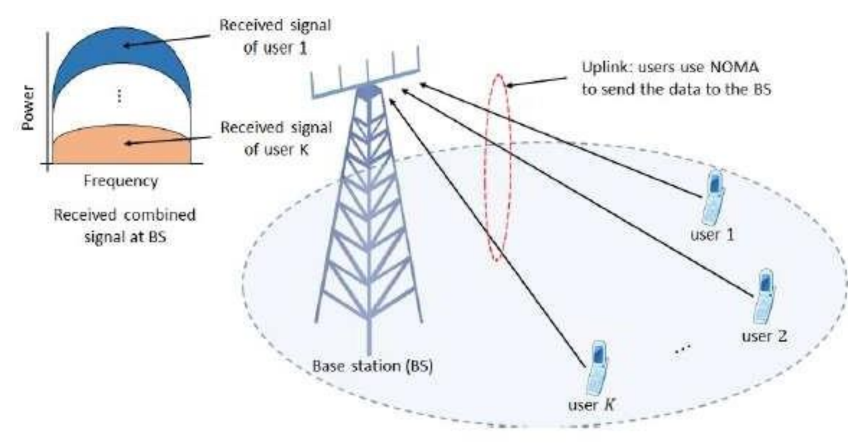


Figure 1. Single cell uplink MIMO-NOMA system

A typical SIC receiver uses a pilot-based channel estimation method which is shown in Figure 2. The two solid lines represent the paths of data symbols and the dash represents the strongest signal. The receiver then decodes the strongest signal from user 1 and then takes it out of the combined signal. The resultant signal is then used to decode the second strongest signal (user 2). The operation is repeated K times until decoding the weakest signal (user K). Let us denote by $Y^D_{-(k-1)}$ $Y^P_{-(k-1)}$ the received combined signal of data (pilot) transmission at the k[th] step of the SIC decoding after cancelling the decoded signals of the previous k-1 users. General channel estimation methods could be used to estimate the channel coefficients $\hat{h}_k$ from the received signal $Y^P_{-(k-1)}$ using the transmitted pilots X^P_k such as Least-Square (LS) or Minimum Mean Squared Error (MMSE) methods. Next, the BS uses the estimated channel $\hat{h}_k$ to detect the desired data signal $\hat{X}^D_k$ of the k[th] user from the received signal $Y^D_{-(k-1)}$. Finally, the transmitted bits $\hat{b}_k \in \{0,1\}^{N \log_2 Q \times 1}$ of user k can be estimated by demodulating the detected signal $\hat{X}^D_k$,where Q is the modulation order of the used digital modulation scheme. For model simplicity, we omit the channel coding and decoding in the second part of the Figure 2. However, in a typical SIC receiver, the receiver would have a pair of blocks for channel coding and one for demodulation. The NOMA system is an interference-limited system. Increasing the number of users makes it harder to use SIC to process multiple signals efficiently. Also, it takes longer to decode the signals. In order to process the weakest signal, the BS has to first decode the signals from all its users. One strategy is to split the users into multiple groups so that the NOMA is applied to each user group and the OMA is divided between the different groups [15]. This method is known as user-pairing and is beyond the scope of this paper.

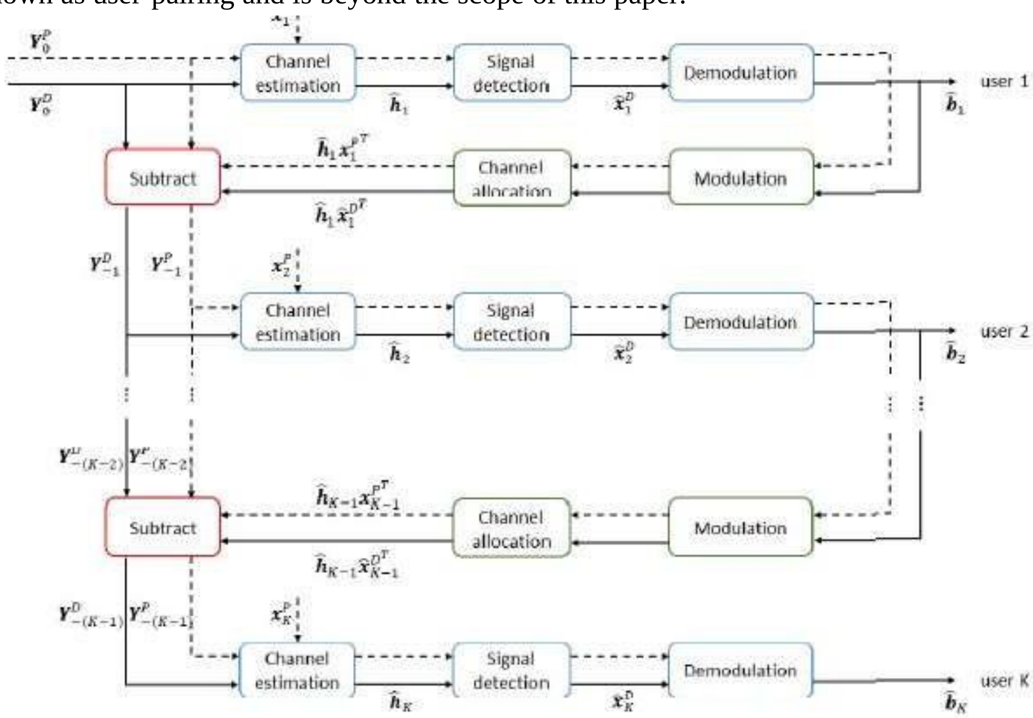


Figure 2: Pilot Channel Estimation using SIC receiver

3. Deep learning mechanism for SIC

In this section, we propose a DL framework to directly decode users' signals without estimating channels parameters or subtracting decoded signals explicitly. The problem is considered as a classification problem in which DNNs are utilized to map the received symbols to transmitted bit sequences. The operation is performed successively in which the signal of a single user is decoded (symbol by symbol) using a separate DNN at each SIC step starting with the user of the strongest signal. The number of nodes in the output layer of the proposed DNN is based on the BPSK Modulation.

Fig. 3(a) describes the proposed DL-based SIC protocol during data transmission. Let us denote by $F_k(.)$ the nonlinear processing function approximated by the k^{th} DNN to decode the user k's signal. All the complex numbers are decomposed into real parts and imaginary parts. Hence, we can define the function of the k^{th} DNN as $F_k(.) = R^{2(M+K-1)\times 1} \to \{0,1\}^{\log_2 Q\times 1}$ that maps the received combined symbol and the previous decoded symbols of all the k-1 users to the transmitted bit sequence of the k^{th} user. Note that this operation is done for N times at each SIC step according to N data symbols.

Compared with the traditional SIC scheme in Fig. 2, the DNN combines the following operations: channel allocation, interference cancellation, channel estimation, signal detection and demodulation. Hence, the proposed scheme can potentially reduce error propagation that might results from channel estimation or subtracting decoded signal from the received combined signal. Each DNN is composed of J fully connected layers followed by an output layer that uses a softmax function (normalized exponential) as the activation function. The softmax function $\sigma(.)$ takes an input vector $z = [z_1,..., z_Q] \in R^{Q\times 1}$ and outputs a vector $t = [t_1,..., t_Q]$ of real values between 0 and 1 given by [16]

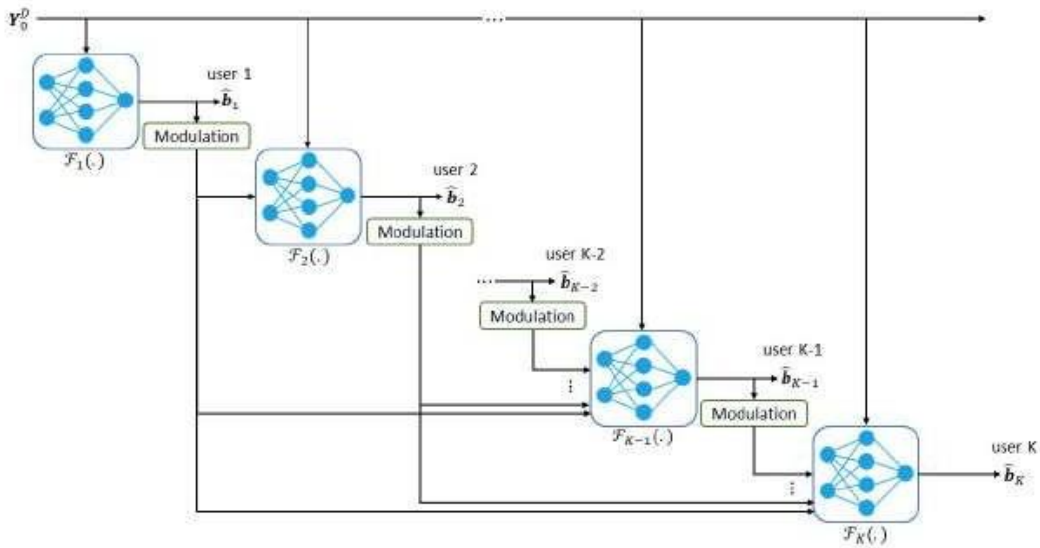
$$t_q = \sigma(z)_q = \frac{e^{z_q}}{\sum_{\ell=1}^{Q} e^{z_\ell}}, \forall q \in \{1,..., Q\}$$

where the denominator $\sum_{\ell=1}^{Q} e^{z_\ell}$ is used for normalization to make sure that $\sum_{q=1}^{Q} t_q = 1$.

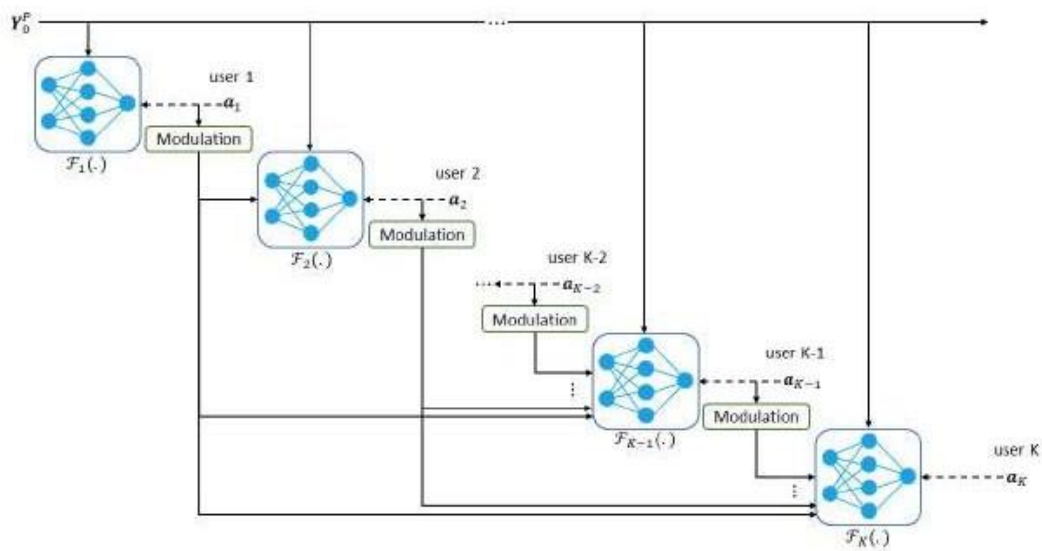
For training, DNN uses L pilot samples at the beginning of each frame before data decoding as shown in Fig. 3(b). Let a^k denotes the transmit bit sequence of the pilot signal of the k^{th} user which represents the training target of the k^{th} DNN (represented by dashed lines in Fig. 3(b)). The DNN's objective is to minimize the categorical cross-entropy loss function between the output value and training target using stochastic gradient descent (SGD) with momentum given by [16].

$$loss = -\sum_{l=1}^{L} \sum_{q=1}^{Q} \beta_{lq} \log(t_{lq})$$

where β_{lq} is a binary indicator ground truth such that $\beta_{lq} = 1$ if and only if the l^{th} sample belongs to the q^{th} class. t_{lq} denotes the probability that the network associates the l^{th} input with class q which actually is the output of the softmax function. After pilot transmission, we acquire the weight matrix W_k and bias matrix B_k of the k_{th} DNN to approximate $F_k(.)$ function, $\forall k \in \{1,..., K\}$ which can be utilized to directly transform the received symbols and previous decoded symbols into transmitted bits $\hat{b}_k$. The W_k is $n_k \times m_k$ weight matrices, where n_k represents the width of the layer k and the m_k represents the width of the layer k-1. B_k is the bias vectors of layer k and layer k-1.



(a) Data transmission (testing phase)



(b) Pilot transmission (training phase)

Figure 3. Proposed Architecture for Deep Learning based SIC

4. Simulation Results

In this section, we conduct an experiment to demonstrate the performance of the proposed DL technique for enhancing SIC. We consider an uplink MIMO-NOMA system with the following parameters: M = 2 antennas, L = 960 pilot symbols, N = 3840 data symbols and P_{max} = 4 Watt. All users use BPSK modulation. For all DNNs of the proposed scheme, we use 2 hidden layers with 100 nodes each. Exponential linear unit (ELU) and rectified linear unit (ReLU) are used as the activation functions of the two hidden layers, respectively. We train the proposed scheme during the pilot transmission with learning rate of 0.001 and training epoch of 0.001 and 100. The performance of the proposed approach is compared with other two methods in terms of bit error rate (BER) and total mean squared error (MSE) under different signal-to- noise ratio (SNR) values. The first method that is used for comparison is another DL-based SIC proposed in [10], namely DL-SIC. The second method is traditional SIC based on zero forcing [17], [18] namely ZF-SIC.

DL-SIC[10]: The architecture of the existing DL-SIC scheme is shown in Figure 4 which is having two parts: The first part is precoder and the second part is SIC decoder.

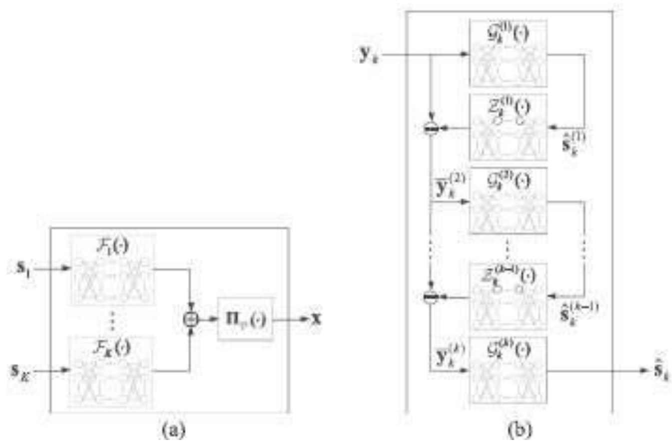


Figure 4: a) Precoder b) SIC decoder [10]

They developed the precoder and SIC decoders using deep neural networks such that the transmitted signals intended to multiple users can be properly precoded at the transmitter based on the superposition coding technique and the received signals are accurately decodable at the users by the SIC decoding.

Assume K = 2, Fig. 5 shows the total MSE between the users' actual signals and their decoded signals given by $\sum_{k=1}^{K} E\{\| X_k^D - \hat{X}_k^D \|^2\}$ for different SNR values. Form Fig. 4, we observe that the proposed technique achieves much lower MSE than both DL-SIC and ZF-SIC, indicating that the proposed scheme learned very well at every SIC step. For a better analysis, Figs. 5 and 6 show the BER versus SNR values for user 1 and user 2, respectively.

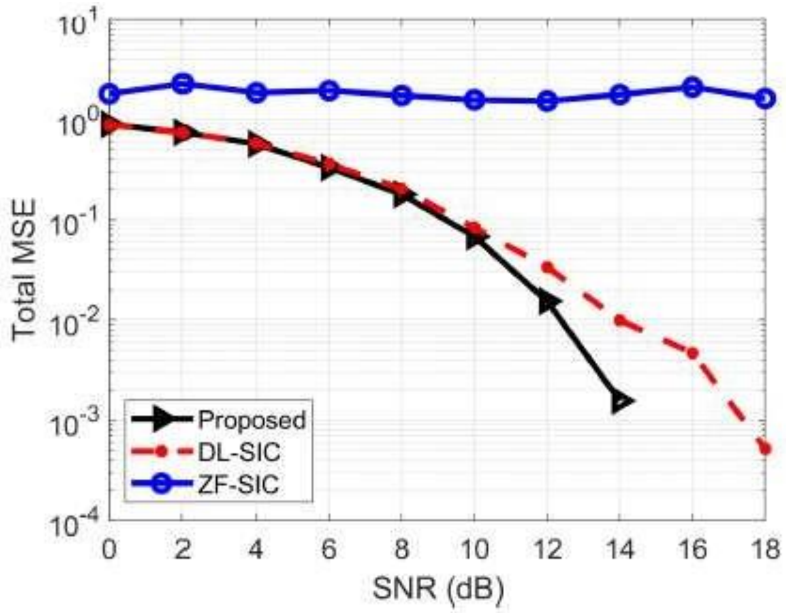


Figure 5. Total MSE versus the SNR for 2 users.

From Fig. 6 we observe that both proposed and DL-SIC have similar performance with low BER compared with ZF-SIC. This is because decoding user 1 signal is done at the first step of SIC since it is the strongest signal. Hence, the corresponding DNNs in both the proposed and DL-SIC techniques can directly learn the decoded signal of user 1 from the received combined signal.

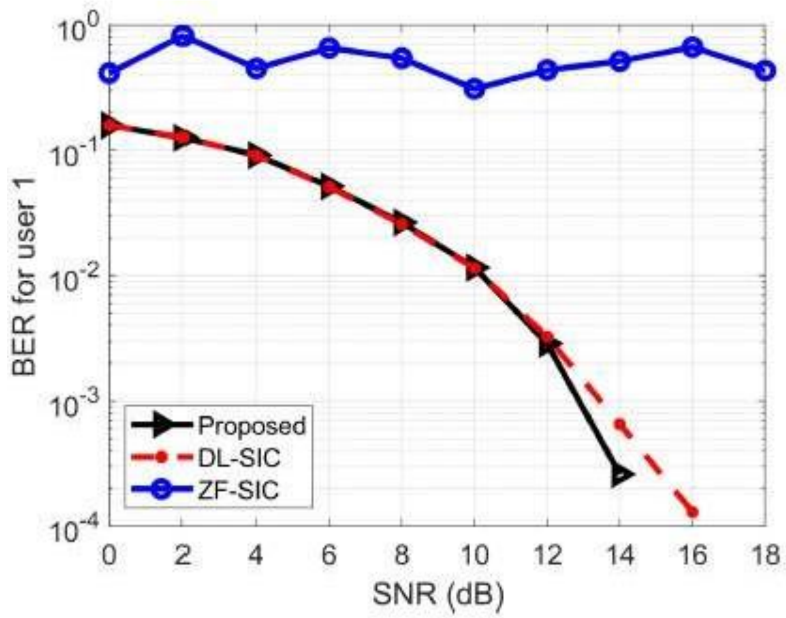


Figure 6. BER for user 1 versus the SNR.

The superiority of our proposed scheme compared with the other DL-SIC appears in Fig. 7 for decoding user 2's signal where it achieves the best BER performance. This because the proposed scheme uses one DNN to directly learn the decoded signal of user 2 from the original received combined signal and user 1 decoded signal, while the DL-SIC algorithm uses 2 DNNs. The first DNN is used to reconstruct the transmitted signal of user 1 so that it can be cancelled from the received combined signal. The resultant signal is then used by the second DNN to decode user 2 signal.

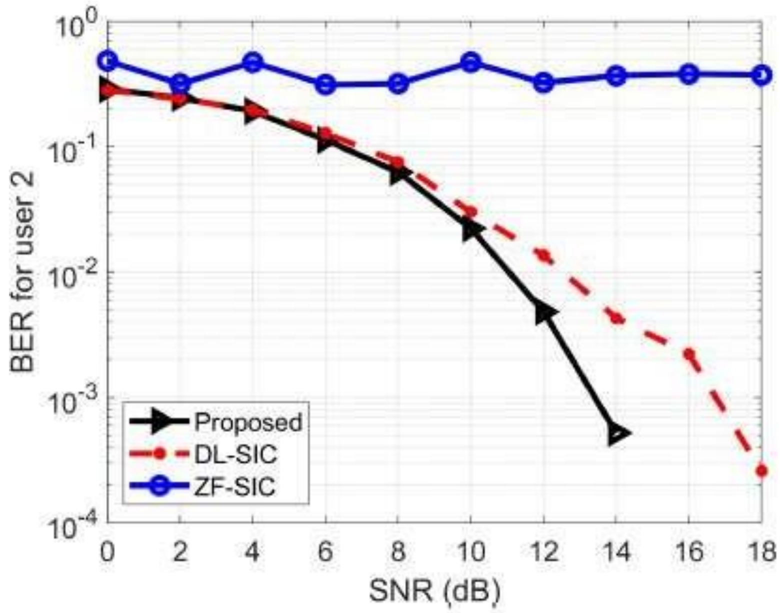


Figure 7. BER for user 2 versus the SNR.

From the above experiment, the advantages of the proposed approach are twofold: first it reduces the computational complexity which could speed-up the consumption time. Specifically, compared with DL-SIC, the proposed scheme uses K-1 DNNs less. This can significantly improve the computational complexity assuming that both schemes have DNNs of the same size. Second it reduces the error propagation in SIC since it directly estimates the decoded signal without any need to estimate the channel coefficients or cancel out decoded signal from the received signal explicitly. This leads to a better performance in terms of BER and MSE compared with other existing SIC methods. This conclusion is confirmed for the case of K > 2 as follows. Figs. 8 and 9 show the MSE versus SNR values for 3 users and 4 users, respectively. Again, the proposed scheme offers significant improvements compared with DL-SIC and ZF-SIC.

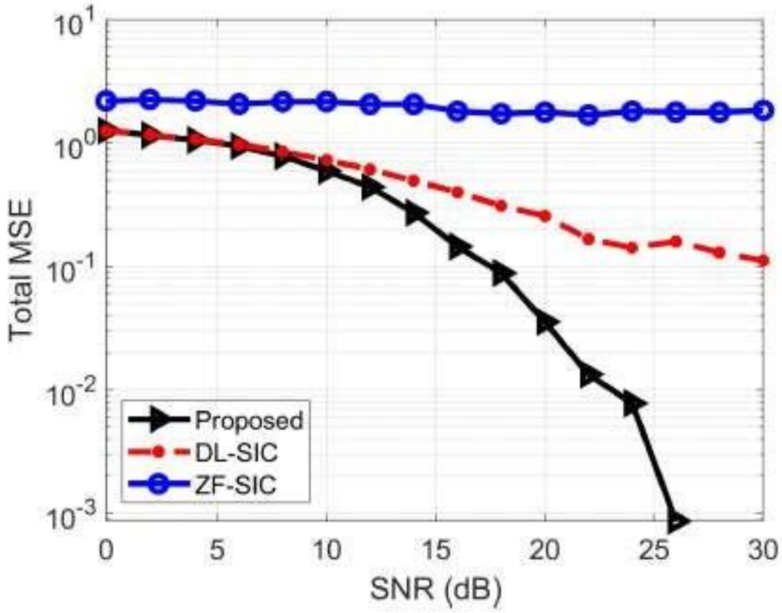


Figure 8. Total MSE versus the SNR for 3 users.

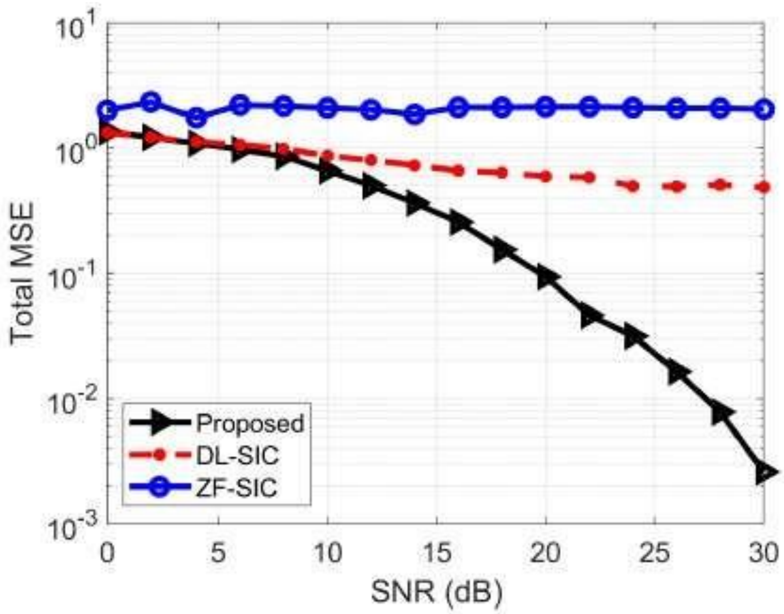


Figure 9. Total MSE versus the SNR for 4 users.

5. Conclusion

A DL-based SIC scheme is proposed that allows a BS to decode multiple users' signals at the same time. The system utilizes a single DNN to perform the task. Each step in the SIC process is connected to a fully-connected layer. The resulting bit sequences are then sent to the corresponding user. The classification problem is usually solved by taking into account the combined signal received by the receiver and the previous decoded symbols. The proposed scheme trains the DNNs to perform a single shot of the user's signal without having to estimate channel coefficients or cancel out the decoded signal. This method can reduce the error propagation in the SIC. According to the simulations, the proposed scheme outperforms the existing SIC schemes for various users. It also offers a reduction in computational complexity compared to other DL-based SIC methods.

References:

[1] Z. Qin, H. Ye, G. Y. Li and B. F. Juang, “Deep Learning in Physical Layer Communications,” IEEE Wireless Communications, vol. 26, no. 2, Apr. 2019.

[2] E. Bj¨ornson and P. Giselsson, “Two Applications of Deep Learning in the Physical Layer of Communication Systems,” arXiv:2001.03350 [cs.IT], Jan. 2020.

[3] S. M. R. Islam, N. Avazov, O. A. Dobre and K. Kwak, “Power-Domain Non-Orthogonal Multiple Access (NOMA) in 5G Systems: Potentials and Challenges,” IEEE Communications Surveys & Tutorials, vol. 19, no. 2, 2nd Quart 2016.

[4] L. Dai, B. Wang, Z. Ding, Z. Wang, S. Chen and L. Hanzo, “A Survey of Non-Orthogonal Multiple Access for 5G,” IEEE Communications Surveys & Tutorials, vol. 20, no. 3, 3rd Quart 2018.

[5] Z. Ding, F. Adachi, and H. V. Poor, “The Application of MIMO to Nonorthogonal Multiple Access,” IEEE Transactions on Wireless Communications, vol. 15, no. 1, Jan. 2016.

[6] Z. Ma, Z. Ding, P. Fan, and S. Tang, “A General Framework for MIMO Uplink and Downlink Transmissions in 5G multiple access,” 2016 IEEE 83rd Vehicular Technology Conference (VTC Spring), Nanjing, China, May 2016.

[7] Z. Wei, L. Yang, D. W. K. Ng and J. Yuan, “On the Performance Gain of NOMA over OMA in Uplink Single-cell Systems,” 2018 IEEE Global Communications Conference (GLOBECOM), Abu Dhabi, UAE, Dec. 2018.

[8] S. J. Nawaz, S. K. Sharma, S. Wyne, M. N. Patwary and Md. Asaduzzaman, “Quantum Machine Learning for 6G Communication Networks: State-of-the-Art and Vision for the Future,” IEEE Access, vol. 7, Apr. 2019.

[9] C. Lin, Q. Chang and X. Li, “A Deep Learning Approach for MIMO-NOMA Downlink Signal Detection,” Sensors (Basel), vol. 19, no. 11, Jun. 2019.

[10] J. Kang, I. Kim and C. Chun, “Deep Learning-Based MIMO-NOMA with Imperfect SIC Decoding,” IEEE Systems Journal, Sept. 2019.

[11] G. Gui, H. Huang, Y. Song and H. Sar, “Deep Learning for an Effective Nonorthogonal Multiple Access Scheme,” IEEE Transactions on Vehicular Technology, vol. 67, no. 9, Sept. 2018.

[12] J. Pan, N. Ye , A. Wang and X. Li, “A Deep Learning-Aided Detection Method for FTN-Based NOMA,” Hindawi Wireless Communications and Mobile Computing, vol. 2020, Jan. 2020.

[13] Z. Wei, D. W. Ng, and J. Yuan, “Joint Pilot and Payload Power Control for Uplink MIMO-NOMA with MRC-SIC Receivers,” IEEE Communications Letters, vol. 22, no. 4, Apr. 2018.

[14] M. Vaezi, R. Schober, Z. Ding, and H. V. Poor, “Non-orthogonal Multiple Access: Common Myths and Critical Questions,” IEEE Wireless Communications Magazine, vol. 26, no. 5, Oct. 2019.

[15] A. B. Reddy and R. Y. R. Kumar, "Performance and Security Analysis in Cloud Using Drops and T-Coloring Methods," 2022 Fourth International Conference on

Emerging Research in Electronics, Computer Science and Technology (ICERECT), Mandya, India, 2022, pp. 1-7, doi: 10.1109/ICERECT56837.2022.10060014.

[16] M. Pischella and D. L. Ruyet, “NOMA-Relevant Clustering and Resource Allocation for Proportional Fair Uplink Communications,” IEEE Wireless Communications Letters, vol. 8, no. 3, Jun. 2019.

[17] C., M., Bishop, “Pattern Recognition and Machine Learning,” Springer, New York, NY, 2006.

[18] Xin Su, H. Yu, W. Kim, C. Choi and D. Choi, “Interference Cancellation for Non-orthogonal Multiple Access Used in Future Wireless Mobile Networks,” EURASIP Journal on Wireless Communications and Networking, no. 231, 2016.