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MIMO-NOMA Systems Channel Performance Using SCMA-Deep Learning Method

Ezhilazhagan Chenguttuvan[1], Lakshmi Prabha Karuppaiah[2], Vinothini V R[3], Sakthisudhan Karuppanan[4*], Nithyadevi Shanmugam[5], Srimathi S[6]

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Abstract: The present research initiatives are based on improved multiple access methodologies with a focus on future wireless communication technologies. A skilled competitor, Non-Orthogonal Multiple Access (NOMA), can be utilized to construct the next generation of wireless communications. When compared to other orthogonal resources, NOMA's main strength is its ability to handle many users. The major NOMA detection method used at receivers for downlink NOMA transmissions is Successive Interference Cancellation (SIC). The receiver complexity and concerns about error propagation are the key limitations of SIC. Deep Learning (DL) is used for downlink NOMA transmission, which is decoded using a Sparse Code Multiple Access (SCMA) decoder. SCMA is used in conjunction with DL to forecast the channel and decode it at the receiver. Two users are provided equal access to resources, notably power, based on their proximity to the base station (BS). With SCMA decoding at the receiver, simulations for AWGN, Rayleigh, and Rician channels were carried out while various constraints were taken into account. SCMA-DL surpasses the MMSE and SIC detection methods in terms of Bit Error Rate (BER) during the decoding phase.

Keywords: *NOMA, Multiple Input Multiple Output (MIMO), Deep Neural Network (DNN), SCMA.*

1. Introduction

NOMA is 100 times faster than 3GPP-LTE in terms of peak data rate. It also has a 1 ms latency, making it 10 times faster than 4th generation networks. The network should have 100,000 devices connected every km, which is 100 times more than what is required for next-generation communication networks. The standard OFDM method for the next generation of wireless networks confines users to sharing all domains, including time, frequency, and space domains [1]. NOMA, which comes in three flavors—power-domain, code-domain, and hybrid-domain—is largely used in wireless communication for MIMO systems in sending and receiving. On the receiver side, signals from various User Equipment (UE) were decoded using a power-domain NOMA technique with SIC. In contrast, it was expected that adopting user-specific spreading sequences might enhance code-domain NOMA approaches to multiplex signals from numerous UEs [2]. Despite the fact that the received signal has severe channel degradation dependent on the UE in the cluster, the receiver decodes it using the SIC method to calculate the UE's channel gain. Channel gain is low. UE signals are given a higher power allocation and are decoded first, whereas UE signals with a lower power allocation are considered interference. A signal is modulated once the higher-power signal has been correctly detected and decoded. The receiving signal is then calculated [3, 4]. This step is repeated until the UE successfully decodes the required data.

The SCMA method, which is a code domain NOMA approach, provides a realistic solution for next-generation wireless networks. SCMA combines spreading and modulation techniques. A codebook containing user-specific data bits that must be converted into multidimensional codewords is delivered to each UE. As a result, the design of the codebook has a significant impact on how SCMA systems operate [3, 5]. To comprehend sparsely organized codebooks that decode overlapped codewords, the Iterative Message Passing Algorithm (MPA) and Maximum Likelihood Decoding (MLD) are widely used. The computing environment's complexity continues to impede SCMAs' ability to work in real-time. System performance has gradually improved as a result of DL techniques in a variety of industries. Deep learning, an advancement in machine learning, has made great progress and is now used in a variety of sectors. Recurrent Neural Networks (RNNs) are used for voice recognition, language modelling, and text production, while Conventional Neural Networks (CNNs) are used for image analysis, and Deep Neural Networks (DNNs) are used for pattern

[1] *Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, India.*
ORCID ID : 0000-0003-3926-9413
[2] *T.S. Srinivasan Centre for Polytechnic College and Advanced Training, Chennai, India.*
ORCID ID : 0000-0002-3282-8094
[3] *Bannari Amman Institute of Technology, Sathyamangalam, India.*
. ORCID ID : 0000-0003-2441-956
[4*] *Dr. N.G.P. Institute of Technology, Coimbatore, India.*
ORCID ID : 0000- 0002-8876-3015
[5] *Sri Krishna College of Technology, Coimbatore, India.*
ORCID ID : 0000-0002-0274-739X
[6] *Saveetha School of Engineering, SIMATS, Chennai, India.*
** Corresponding Author Email: drkssece@gmail.com*

identification and classification [6]. CNNs are designed particularly for image and video data, but DNNs can handle a wide range of data sources, including time series data, audio signals, and text. Its high classification and identification characteristics make it ideal for dealing with wireless communication system difficulties such as synchronization, channel estimation, iterative decoding, and multi-user decoding. Because DNNs can cope with multidimensional values with nonlinear characteristics, they are also helpful for analysing the receiver signal and creating the SCMA codebook. With the SCMA system, DL has been employed to overcome codebook design and decoding problems [4,5]. The performance of DL-based techniques in terms of BER is encouraging.

NOMA could be combined with other wireless communication technologies in the future to meet needs for massive connectivity, high spectral efficiency, improved energy efficiency, significant achievable data rates, low latency, exceptional user fairness, high throughput, ultrahigh reliability, and adherence to a variety of Quality Standards (QS) [7]. The SIC used at the receiver influences error propagation and receiver complexity based on the number of UEs [8]. We present an SCMA-DL technique for improving MIMO NOMA system performance by successfully reducing complexity and decoding the received signal. The benefits include enhanced communication system performance and a reduction in reference signal overhead, which boosts downlink system throughput.

In NOMA, superposition coding is employed at the transmitter so that the SIC receiver can distinguish between users in the uplink and downlink channels [9]. Other signals in the area frequently distort received signals. This problem is addressed by the "SIC" algorithm. The intra-beam interference in NOMA is eliminated by using the SIC technique to decode the combined signals received at the receiver. The idea behind SIC is the successive decoding of the superposed signals. When two or more signals are received simultaneously by the SIC in a UE receiver, the strong signal is initially decoded, after which it is subtracted from the superposed signal, and the weak signal is then recovered. Knowing which UE will conduct SIC on the downlink is crucial. NOMA is occasionally thought of as the decoding direction. In a nutshell, the UEs' rising channel gains from a specific BS determine this orientation. Based on the sequence [10], the Near User (NU), who has a high channel gain, decodes the signal from the Far Users (FUs), who have a low channel gain. After signal decoding, NU employs SIC to remove pointless signal data. The concept of NOMA using SIC for downlink is illustrated in Fig. 1.

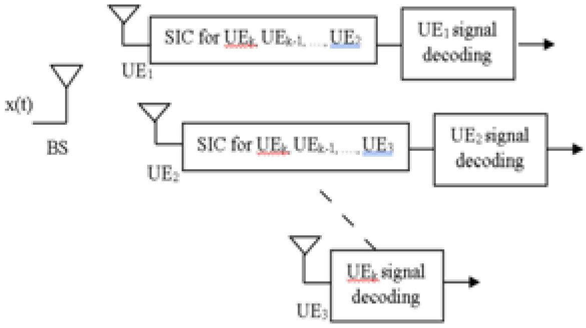

Fig. 1. NOMA using SIC for downlink

According to speculation, NU does not fully comprehend the specifics of the FU signal. As a result, it is anticipated that the NU cannot completely remove the FUs' interference. If the decoding procedure is flawless, a waveform accurately relating to only that particular transmission can be generated by subtracting the signal that is first decoded from the signal that was received [11]. You keep doing this until you find an accurate signal. The serial input converter repeats this procedure until it finds the desired transmission. NOMA implementation in wireless networks requires a lot of computer resources for the SIC and power allocation processes. The following are the primary contributions of this study:

1. To the best of our knowledge, we developed the DL-based downlink MIMO-NOMA detecting system. Instead of using a SIC receiver, the proposed system may directly process the conventional MIMO-NOMA signal. We make full use of DNN's capacity to handle higher dimensional data. The DL-based technique has the potential to improve detection efficiency.

2. The MIMO-NOMA-DL system can decode the signal after estimating the channel characteristics. Instead of thinking about channel estimation and signal detection as independent processes, they can be combined.

2. Proposed System

This system will learn how to use DL-based techniques to identify various channel restrictions when using various channels and take performance into account while using various channel configurations. By transmitting the known pilot signal and using these pilot symbols, the Channel Estimation technique is put into practice [12]. The remaining channel response is then interpolated. In this case, channel estimation is performed using deep learning techniques. We recommend using a DL detector to find MIMO-NOMA signals. Without further signal processing, the received signal is transmitted directly to the MIMO-NOMA-DL detector. MIMO-NOMA-DL [13] is the simplest and most efficient solution to replace the SIC receiver. The pilot signal, which is a known signal, is transmitted by the transmitter to the receiver together with the data signal. Pilot signals are unique to each user and can be easily separated from the data signal. These signals can be used to estimate the channel coefficient, which depicts the magnitude and phase of each user's transmitted and received signals. For the purpose of decoding the user's data signals, the channel coefficient is offered [14].

2.1. SCMA Over SIC

The received signal is continuously processed in SIC receivers in order to eliminate the interference brought on by individual users. The multi-user detection approach is employed in the SCMA detector.

Better Spectral Efficiency: SCMA delivers higher spectral efficiency than SIC, allowing more users to send data over the same frequency.

Complexity and Latency: In SIC, complexity rises with the number of users because SIC decodes the signals of each user individually, which is time-consuming, but the SCMA decoder can decode the signals of many users concurrently, which reduces latency.

Flexibility: SCMA increases performance by assigning a particular codebook to each user based on the user's transmission characteristics. However, in SIC, the receiver occasionally needs each user's signal structure, which is impossible.

Our primary goal is to create SCMA decoders. The DL-based decoder for an SCMA system produces outputs tailored for J users and components using k resources. The labels or symbols associated with each output correspond to the numbers 1, 2,..., K. Our goal is to predict the input symbol bi for m = 1, 2,..., I in the received signal. This test is really challenging because the channels are fading and loud. The DL technique is used to decode the SCMA signals. We propose a neural network that learns its model parameters from training data and applies them to anticipate the symbols in the input data. In Fig. 2, the SCMA model is depicted.

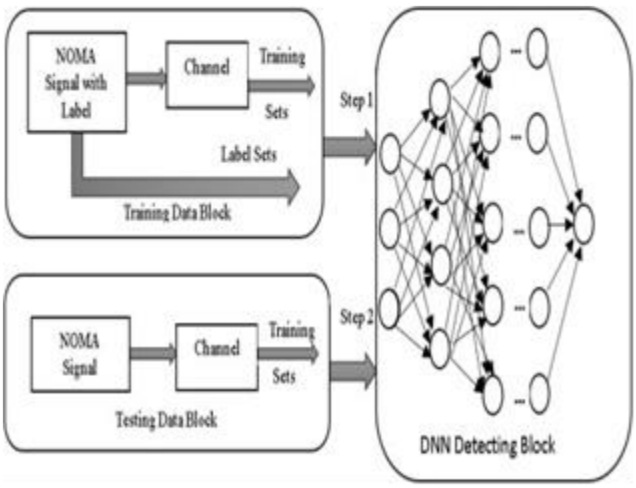

Fig. 2: Proposed SCMA-DL model

The transmitted signal vector **x** represents a linear combination of the sparse code vectors for each user:

$$\mathbf{x} = \sum \mathbf{s}j\mathbf{b}j \qquad \text{---(1)}$$

where **s**j is the sparse code vector for user j, and **b**j is the modulated symbol for user j.

The equation for mapping the user's message bits onto the sparse code is expressed as:

$$X = f(B) \qquad \text{---(2)}$$

where X is the sparse code matrix with dimensions K x M, where K is the number of users and M is the number of code words in the codebook; B is the message bit vector with dimensions L x 1, where L is the number of message bits per user.

The equation for SCMA in MIMO-NOMA can be expressed as:

$$y = \mathbf{H}x + \mathbf{n} \qquad \text{---(3)}$$

where **y** is the vector of received signal, **x** is the vector of transmitted signal, **n** is the noise vector, and **H** is the channel matrix [15].

The decoded signal is obtained by estimating the transmitted signal vector x by using the received signal y and the channel matrix H, and then the message bits are recovered from the estimated transmitted signal vector x. The equation (4) for the estimated transmitted signal vector x in a MIMO-NOMA system can be expressed as:

x = argmax ||y - Hx||^2 + lambda * ||x||_1 ---(4)

where argmax is the argument that maximizes the expression, ||.|| is the Euclidean norm, lambda is the regularization parameter, and ||.||_1 is the L1 norm.

The message bits are obtained by de- mapping to the estimated transmitted signal vector x. This can be expressed as:

b = f^-1(x) ---(5)

where f-1(.) denotes the inverse mapping of the codebook, and b is the recovered message bits.

2.2. MIMO-NOMA DNN Model

The three essential components of the MIMO-NOMA-DL system are the training, testing, and DNN detection blocks. For a number of users, DNN and the data are trained and tested [16]. Fig. 3 below provides an illustration of the MIMO-NOMA-DL standard's structure. The DNN's training block generates the MIMO-NOMA signal with labels. The testing block is used to simulate real-time MIMO-NOMA transmission. first detecting block When the online operating block is disabled during a training program, the offline training block is enabled. Two components make up the input to the DNN training system: the observed data provided by the labels, which aid the DNN in optimizing its parameters, and the input layer provided by the received NOMA signal for the DNN system. Input, output, and hidden layers are included in the DNN model for the detection of MIMO-NOMA signals. The input layer detects the MIMO-NOMA signal. To get around the vanishing gradient problem with the sigmoid function, the entirely connected layers are what make up the hidden layers. By combining the output layers, the signals from numerous antennas are decoded in a single slot.

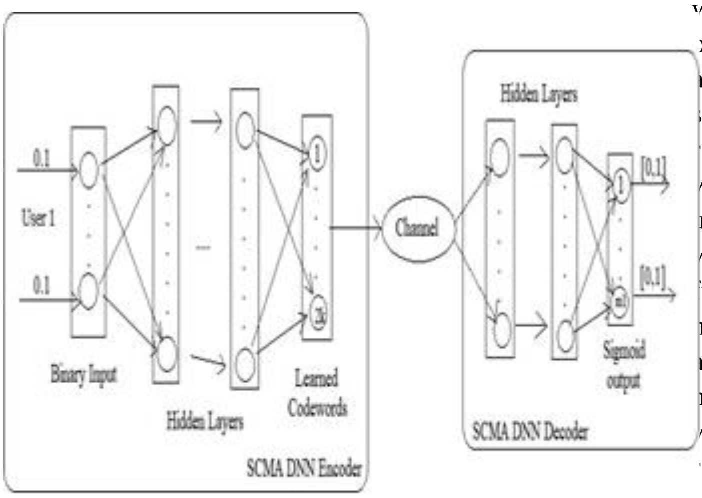

Fig. 3: MIMO-NOMA DL model

2.3. SCMA-DL

We take into consideration that J denotes the SCMA system's available users and K denotes the resource blocks available for the downlink SCMA system. Due to the sparse form of the system, each user is given a sparse code that extends to K resource blocks. The SCMA system may experience overload if the user-to-resource block ratio, denoted as λ=J/K, is too high. A constellation diagram rotation mechanism is used at the transmitter to create a special user codebook in order to address this. At the receiving end, the received signal is decoded using DNN. Utilizing the DNN's hyperparameters, it is able to study the channel parameters and MIMO-NOMA decoding technique. The DNN detecting block should contain the number of layers, activation function, loss function, and optimization criteria iteration method as part of it. The first two sections deliver channel labels and signals, while the final block restores the original data [17]. In light of this, the detection procedure can be split into two phases:

Phase 1: Training Scheme:

At the receiver, the received signal r can be expressed as the sum of the channel vectors hj and codewords tj of each user j, as well as additive white Gaussian noise n with zero mean and variance σ2 [18].

$$r = \sum_{j=1}^{J} diag\left(h_j\right) t_j + n \quad --- (6)$$

We observe that an encoder (codebook) created the codeword tj from the user j's input data symbol bj. The aim of the SCMA decoder is to reconstruct the input symbol bj for each user from the received signal r. A DNN consists of several layers called "neurons" which are composed of nodes. The computation takes place at a node, that can express as:

$$y = \varphi \, (wTx + b) \quad ---(7)$$

y represents the output of a neuron in the DNN. φ represents the activation function, which helps us decide whether the neuron should excite or not i.e., whether its output should be a 1 or a 0. w represents the weight assigned to each input signal. In the MIMO NOMA system, each input signal is a different user's signal. x represents the input signals sent by each user. In other words, x is a vector that contains the signals sent by each user. b represents the bias term, which is added to the weighted sum of the input signals before the activation function is applied. A DNN consists of more than one hidden layer in addition to input and output layers. The architecture of DNN includes layers, where each layer is made up of Nl,o nodes that connect to the previous layer with Nl,i nodes. This layer can be mathematically represented as:

$$yl = \varphi l \, (WlTxl + bl) \qquad ---(8)$$

where in a DNN, each layer has an input vector x1 ∈ R Nl,i and an output vector y1 ∈ R Nl,o. The layer's weight matrix is denoted by W1 ∈ R Nl,i × Nl,o, and the bias vector is represented by b1 ∈ R Nl,o. The DNN structure is illustrated in Fig 4.

Phase 2: Testing Strategy:

Following DNN training, testing mode is turned on. In phase 2, the offline block is suspended and the online operating block is given access to the DNN system. The process' efficacy is assessed at this stage.

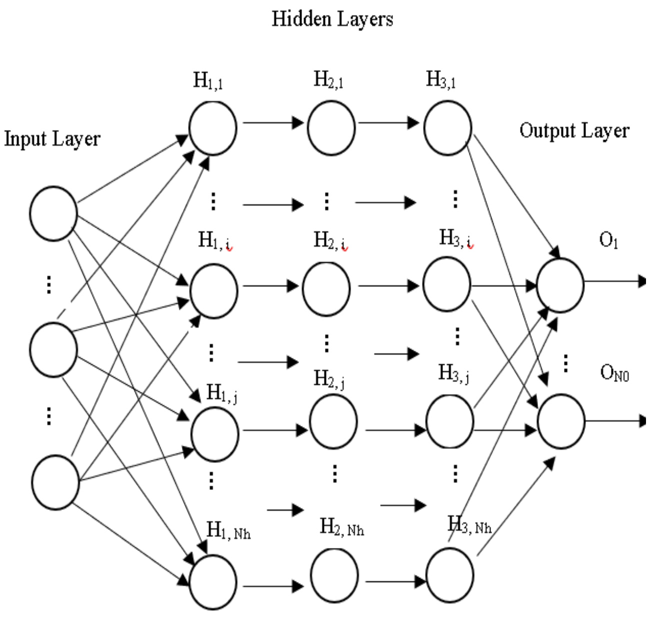

Fig. 4: Structural layers of DNN

2.4. Algorithm

The user information is produced for transmission. Each user receives a subcarrier according to their channel circumstances.

Each user is given a distinct sparse code, and the weight given to each user is multiplied by the code's value.

The sparse code is then modulated using the QPSK modulation technique.

After that, an SCMA encoder is used to encrypt the modulated signals.

Each user is given a certain amount of power and time slots according to the channel requirements. After the signals are multiplexed and mapped onto a channel, the receiver uses a pilot system to estimate the channel conditions.

Each user's received symbols are processed, and the data is then decoded in order to identify the user's sparse code.

3. Results and Discussion

Continue to discuss the simulation results and performance comparisons of different channels with NUs and FUs for AWGN, Rayleigh, and Rician channels using SCMA-DL and comparison of SCMA-DL with SIC and MMSE.

Table 1: Parameters and respective values used for the simulation

PARAMETERS	VALUES
Number of UEs	2
Modulation	QPSK
Number of Subcarriers	64
Channel	AWGN, Rayleigh, and Rician
Input and Output layers	1
Hidden layers	3
Number of training samples	6,000
SNR	10–20 dB
Mini batch size	4000
Max Epochs	50

Table 1 provides various parameters and their respective values for a neural network model trained to perform a specific task.

3.1. Simulation Results

Fig. 5 displays the simulation output of SCMA-DL method for Rician fading channel. The simulated results indicate that UE 1 which is NU is produces a BER of 0.0004 for the SNR value of 16 dB whereas the UE 2 which is FU produces BER of 0.0114 for the SNR value of 28 dB.

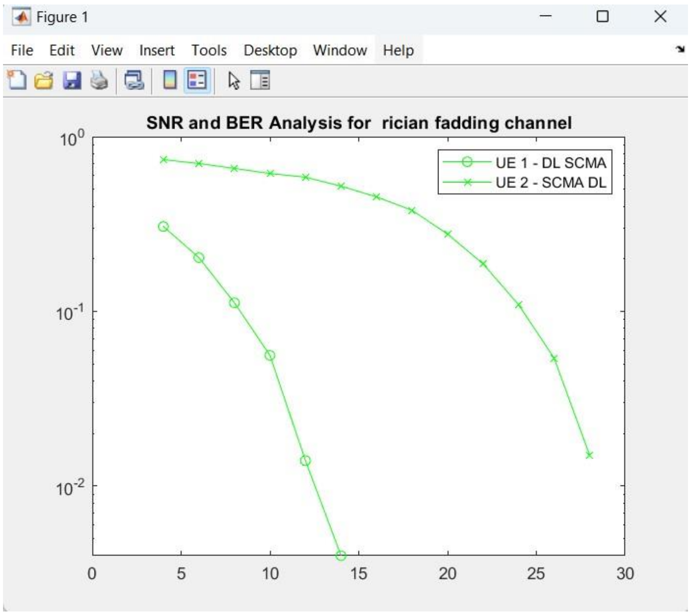

Fig. 5: BER vs. SNR analysis of the Rician Channel

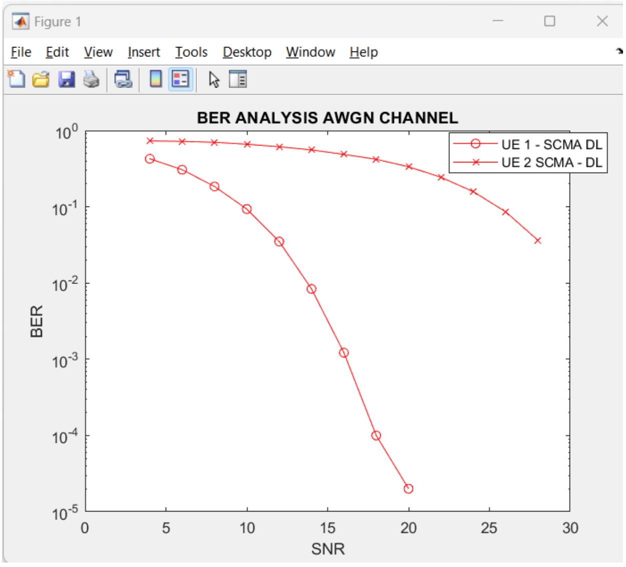

Fig. 6: BER vs. SNR analysis of the AWGN channel

Fig. 6 displays the outcome of the SCMA-DL approach for the AWGN channel. In this scenario BER performance is evaluated for two users UE 1 and UE 2. The simulation results show that UE 1 which is NU produces BER of 0.000066 at SNR value 20 dB and UE 2 which is FU produces BER of 0.036 at SNR value of 28 dB.

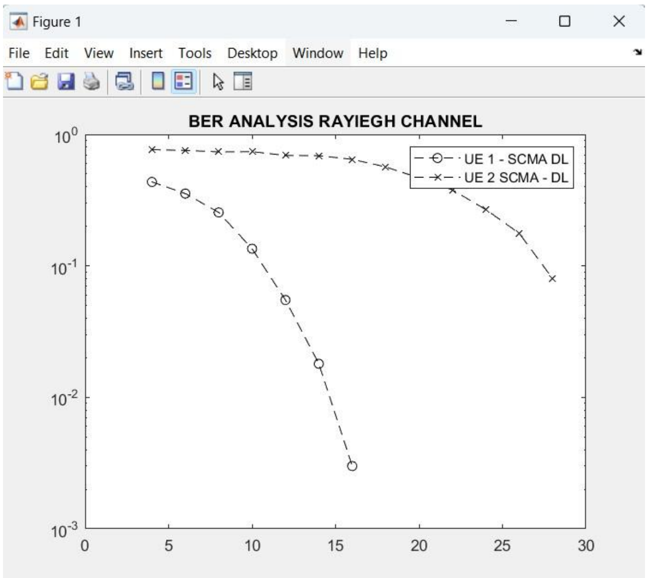

Fig. 7. BER vs. SNR analysis of Rayleigh Channel

Fig. 7 displays the outcome of the SCMA-DL approach for the AWGN channel. In this scenario BER performance is evaluated for two users UE 1 and UE 2. The simulation results show that UE 1 which is NU produces BER of 0.000066 at SNR value 20 dB and UE 2 which is FU produces BER of 0.0036 at SNR value of 28 dB.

Table 2: The value of BER and SNR of the Rayleigh, Rician, and AWGN channels

Channel	UE 1 (NU)		User 2 (FU)	
	SNR (dB)	BER	SNR (dB)	BER
Rayleigh	20	0.00013	28	0.087
Rician	16	0.0004	28	0.0114
AWGN	20	0.000066	28	0.0036

The Rician fading channel, AWGN channel and Rayleigh fading channel are commonly used in wireless communication systems. These three channels represent different propagation conditions which are useful in analyzing communication systems. Table 2 shows the performance each channel under different constraints. The AWGN channel performance is better due to fading effects are negligible compared to Rician and Rayleigh channel.

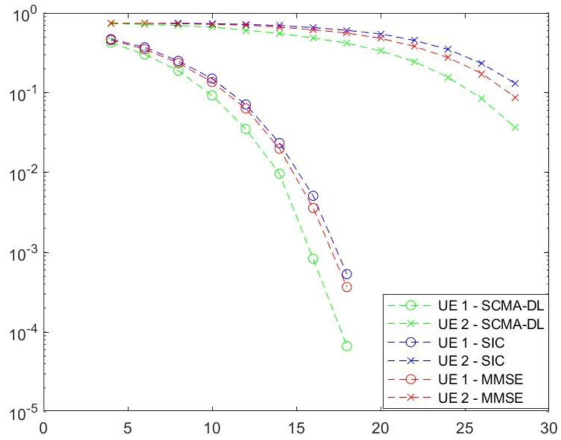

Fig. 8. BER vs. SNR Comparison of MMSE, SIC, and SCMA-DL

Simulation results of SNR vs BER for the AWGN channel using MMSE, SIC, and SCMA-DL methods is shown in Fig.8. It is observed that both UE 1 and UE 2 performance using SCMA-DL method outperform SIC and MMSE methods. MMSE method is used to mitigate the effects of noise and interference in communication systems. However, in the comparison with SCMA-DL, it appears to have lesser BER values, indicating inferior performance in the AWGN channel. SIC is a multi-user detection technique commonly used in wireless communication systems to decode multiple users' signals in an interference-limited environment. However, the simulation results show that the SIC method performs worse than the SCMA-DL method for both UE 1 and UE 2 in the AWGN channel, as evident from the higher BER values. The SCMA-DL method is a combination of SCMA, a non-orthogonal multiple access technique, and deep learning algorithms to improve the performance of the communication system. Table 3 shows the SNR & BER values of MMSE, SIC and SCMA-DL methods.

Table 3: The value of BER and SNR for MMSE, SIC and SCMA-DL in AWGN Channel

Method	UE 1 (NU)		User 2 (FU)	
	SNR (dB)	BER	SNR (dB)	BER
MMSE	20	$4e^{-05}$	28	0.133
SIC	20	$1e^{-05}$	28	0.088
SCMA-DL	22	$1e^{-05}$	28	0.037

4. Conclusion

The potential benefits of DL-aided communication motivated us to conduct research on a cutting-edge DL-based strategy to enhance SCMA systems' BER performance. The combination of DL-based method in MIMO-NOMA and simultaneous channel estimation opens up new possibilities for efficient and robust communication systems. The experiments conducted in Rayleigh, Rician, and AWGN channels demonstrate that DL-based method outperforms previous methods. This improvement in BER performance indicates that this approach is effective in mitigating the effects of fading and noise in the wireless channels. This eliminates the need for complicated algorithm design and manual fine-tuning, making the implementation and deployment proposed method is easier. The channel estimation and signal detection processes can be completed simultaneously using the proposed method. According to the simulation results, both UE 1 and UE 2 achieve better BER values using the SCMA-DL method compared to the MMSE and SIC methods. This suggests that SCMA-DL provides superior performance in the AWGN channel, possibly due to its ability to better handle interference and noise in a multi-user scenario. In future, MIMO-NOMA can enhance spectral efficiency and capacity, while DL-based signal detection can further improve performance, resulting in an advanced and high-performance communication system.

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Author Contribution(s): The corresponding author carried out the conceptualization. The first and second authors contributed to the implementation of the concepts. All the authors contributed in writing the manuscript, proof reading and approved the final manuscript.

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Competing Interests

The authors declare that they have no competing interests.

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