# Enhancing Energy Efficiency and Data Rate in MIMO-NOMA Systems Based on Communication Deep Neural Networks for 6G Communications

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Abstract: The emergence of 6G communication networks requires novel techniques to deliver massive connectivity with high data rate, and enhanced energy efficiency, driving the future of communication systems. The integration of Non-Orthogonal Multiple Access (NOMA) with Multiple-Input Multiple-Output (MIMO) systems, offers a promising solution to enhance system energy efficiency and data rate. Rapidly changing channel conditions and complex spatial structures degrade system performance and limit its applicability. To address these restrictions, this article proposes a deep learning-based MIMO-NOMA framework that maximizes data rate and energy efficiency. Specifically, we develop a novel Communication Deep Neural Network (CDNN) architecture comprising multiple hidden layers and convolution layers. The deep learning techniques such as, the CDNN framework uses training algorithms to solve the power allocation problem and increase MIMO-NOMA's energy efficiency and data rate. Furthermore, simulation results demonstrate that the suggested CDNN framework has better data rate and energy efficiency than the Secondary BS-aided scheme, ɑ- fairness aided based scheme, LSTM-NOMA based scheme and basic deep learning scheme. The Secondary BS-aided scheme data rate mean is 2.4586, fairness aided based scheme mean is 2.4986, LSTM-NOMA based scheme mean is 2.5343, deep learning scheme mean is 2.6571 and proposed CDNN scheme data rate mean is 2.8514. So that proposed CDNN framework has higher energy efficiency and data rate than compared to other regular methodologies.

## 1 INTRODUCTION

6G boasts significantly higher data rates, lower latency, and massive connectivity compared to 5G and 4G. Key technologies driving these advancements include MIMO and millimeter-wave communication, which also enhance capacity, reliability, and scalability (Andrews et al. 2024). MIMO employs multiple antennas at base stations to improve cellular network uplink and downlink performance. The MIMONOMA system further boosts efficiency and data rates (Hoydis et al. 2024). NOMA enables multiple clients to share the same frequency resources using power domain multiplexing. Combining NOMA with Orthogonal Multiple Access (OMA) techniques yields enhanced spectrum efficiency and high reliability, supporting massive connectivity and outperforming OFDMA (Chiu et al. 2025). For millimeter-wave massive systems, a novel beam space concept for MIMO minimizes the number of required frequency chains without compromising performance (Wang et al. 2024). To enhance channel and signal estimation in orthogonal frequency division multiplexing systems, deep learning techniques are applied (Ye et al. 2024). By incorporating Machine Learning (ML) concepts into the wireless core and edge infrastructure, next-generation wireless communication systems can provide IoT devices with ultra-reliable, low-latency interactions and ubiquitous connectivity, driven by intelligent, data-driven capabilities (Chen et al. 2025).



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# 2 RELATED WORKS

Over 200 articles in IEEE Xplore and 95 in academia.edu have been published on MIMO-NOMA system in past four years. To provide a deep learning framework and optimize the MIMO-NOMA system's energy efficiency and data rate after thorough investigation. To achieve improved power allocation performance for energy efficiency and data rate optimization, the initial step is to merge deep learning with MIMO-NOMA systems (Ding et al. 2024). The capacity gains achievable by MIMO-NOMA over MIMO-OMA, showing that NOMA can provide higher spectral efficiency and greater system capacity than OMA (Zeng et al. 2024). To optimize and enhance the performance of NOMA systems. By applying deep learning, the paper aims to improve key tasks such as signal detection, interference cancellation, and channel estimation, ultimately enhancing spectral efficiency and reducing bit error rates (BER) in NOMA systems (Gui et al. 2024). Downlink multiuser MIMO systems' NOMA, along with improvements in beamforming, power allocation, and user clustering, all of which are crucial for enhancing system performance. The suggested CDNN scheme's data rate cluster has a learning rate of 0.002, 0.001, 0.01, 0.1 (Ali et al.2024). Maximum data rate and energy efficiency are provided by a deep learning-based NOMA system with MIMO (Huang et al. 2024). LSTM based NOMA further develops aggregate rate, diminishes idleness, and improves power assignment. The framework accomplishes total rate: 2.8 Gbps (17% higher than customary NOMA) Inactivity decrease: 90% and Better reasonableness for clients with powerless channels (Huang et al. 2025). It is understood that NOMA is important the contrast between two channel gains is exceptionally huge. A crafty lattice precoding calculation defeats the constraints of customary NOMA in non-distinct channels by: Adjusting power assignment in view of channel relationship. Upgrading the aggregate rate by 13% contrasted with regular NOMA. Further developing decency by expanding major areas of strength for the rate (Saito et al. 2024). The proposed calculation for force and sub-transporter designation is gotten from the non-raised power minimization under rate and sub-transporter reservations, for which an ideal arrangement is NP-hard. The proposed MIMO-NOMA accomplishes 35% power productivity improvement over OMA, 51% better range productivity, 41% higher total rate than OMA (Tweed et al. 2025).

From previous findings, it is concluded that energy efficiency and data rate is increased. The aim of the study is to further develop the data rate and energy efficiency between CDNN and deep learning approaches.

# 3 METHODOLOGY

Consider a standard downlink MIMO-NOMA system consisting of a single base station with a uniform, linear array of M antennas and D multi-antenna users. Assume Rayleigh fading in the downlink channel. Each user is equipped with Nr receiving antennas, and it is assumed that the base station has no knowledge of each user's individual channel. To adopt NOMA principles in the MIMO system, users are randomly grouped into M clusters, each containing N clients (i.e., D = MN). The transmitted signals at the base station can be represented by the equation (1)

$$Y = H\ s \tag{1}$$

where H is a M × K precoding matrix, then s is further formulated in equation (2) as

$$s = \begin{pmatrix} \beta 1,1\ s1,1 + & \cdots & \beta 1, Ks1, K \\ \vdots & \ddots & \vdots \\ \beta K, 1sK, 1 & \cdots & \beta M, KsM, K \end{pmatrix} \left[ \begin{bmatrix} S1 \cdots \\ SM \end{bmatrix} \right] \tag{2}$$

Here, sM,K is the information carrying signal that is received by the N-th client of the M-th cluster, Where βi,j is a power allocation coefficient of NOMA.

## 3.1 MIMO-NOMA System

A deep learning-based MIMO-NOMA system integrates MIMO-NOMA system with Deep Neural Network (DNN), leveraging cutting-edge deep learning techniques to develop a method that optimizes the sum of energy efficiency and data rate. To enhance performance, a kernel-based Communication Deep Neural Network (CDNN) is designed to approximate the MIMO-NOMA system's power allocation optimization problem. The base station implements the trained CDNN, which assigns a distinct power to each user. The characteristics of the channel links and clients are used as input features, without physically modeling the users in the CDNN architecture. As a result, the training examples incorporate information about client and channel conditions, improving efficiency.

A proposed CDNN framework is used to estimate the system, using different convolutional and welldesigned hidden layers (Fig.1.) that use certain activation functions to compute. Moreover, from the proposed CDNN structure, a new power distribution strategy is presented for enhancing the energy efficiency and data rate performance. The technique can improve energy efficiency and data rate. Figure 1 shows the Multiple clusters of MIMO-NOMA system.

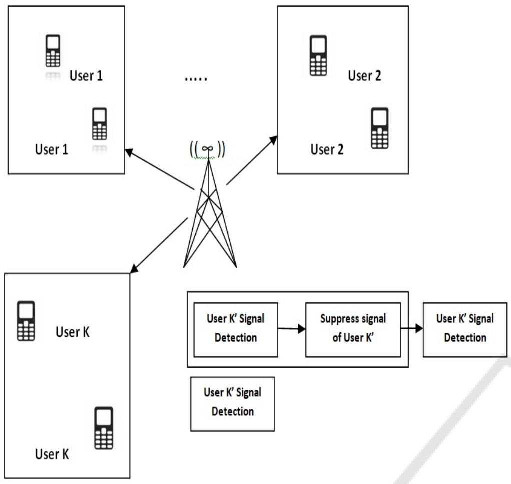


Figure 1: Multiple Clusters of MIMO-NOMA System.

## 3.2 MIMO-NOMA System with Deep Learning

The goal is to optimize the data rate and energy efficiency of the MIMO-NOMA system. The data rate of the N-th user in the first cluster is obtained in this equation (3) and is represented by

$$K1, M = \log_2(1 + \gamma N1, M) \tag{3}$$

The Figure 2 represents the workflow for optimizing deep neural networks involves a multi-step process data sampling, training subsets, and fitness evaluation.

The process begins with the initialization step, where random values are assigned to represent the starting conditions of the algorithm. The fitness or effectiveness of the current configuration is evaluated based on specific criteria, such as model accuracy or other performance metrics. A decision is made based on whether predefined conditions are met. If these conditions are not met, the system proceeds the data for variation step, where adjustments are made to the dataset or sampling method to improve performance. If the conditions are met, the system progresses to the next step.

The process starts with the original database, which serves as the basis for creating subsets and adjusting weights. The weights of the dataset are adjusted to emphasize or de-emphasize specific samples, allowing for better training of models on critical data points. The dataset is split into multiple subsets (e.g., A, B, C) with adjusted sample weights to ensure diverse training. Each subset is used to train separate deep neural networks. It evaluates each trained network and identifies the optimal one based on predefined criteria, such as accuracy, loss, or generalization performance.

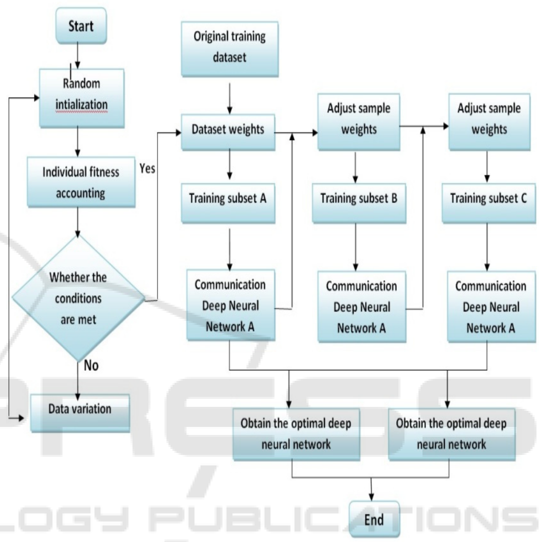


Figure 2: Flowchart of Deep Neural Network Optimization.

## 3.3 CDNN Based MIMO-NOMA System Architecture

This framework (Figure 3) comprises 11 convolutional layers and a max-pooling layer along with fully connected layers, the architecture is denoted as (Conv, FC, MaxPool, S), where the architecture comprises convolutional layers (Conv), fully connected layers (FC), and max-pooling operations (MaxPool) with specified strides (S). Furthermore, the precoding matrix P is composed of individual precoders for each antenna. The output precoder, denoted as p̄ m, along with its associated power allocation factors, produces the optimal power allocation results.

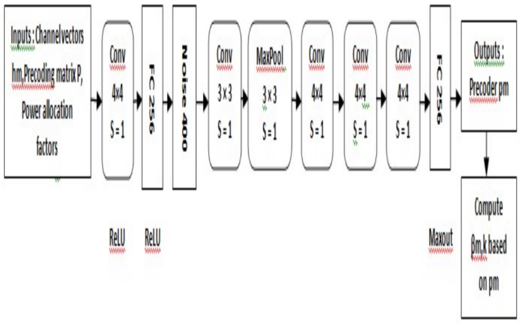


Figure 3: CDNN Based Deep Learning for Mimo- Noma System.

# 4 SIMULATION RESULTS AND ANALYSIS

The simulation was based on improving energy efficiency and data rate using the communication deep neural network method, and using Communication toolbox includes simulink blocks in MATLAB to plot the efficiency and data rate. The Sample data was established based on previous study results (Huang, Yang, et al., n.d.).

## 4.1 Comparison Data Rate with SNR


Figure 4: A Comparative Analysis of the Data Rate Performances Is Presented, Evaluating the Proposed CDNN Scheme Against Existing Approaches, Including the LSTM-NOMA Based Scheme, A-Fairness Based Scheme, and Secondary Bs-Aided Scheme.

The Figure 4, compares data rate performances of different approaches next to SNR (dB). The proposed CDNN-based approach achieves the highest data rate, followed by the deep learning approach and NOMA-based LSTM scheme. The α-fairness based scheme performs moderately, while the Secondary BS-aided scheme has the lowest data rate.

## 4.2 Comparison Data Rate per Cluster with SNR

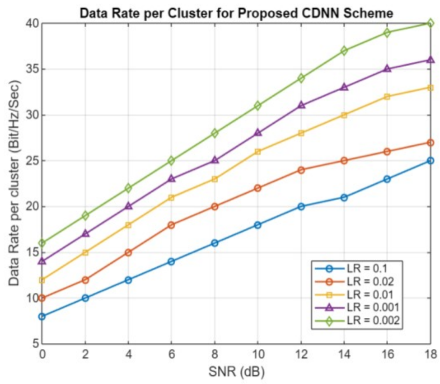


Figure 5: Comparative Analysis of the Data Rate Per Cluster with Different Learning Rates.

The Figure 5, Illustrates the data rate/cluster for the future CDNN scheme with different learning rates (LR). As SNR increases, the data rate also improves for all learning rates. A lower learning rate (LR = 0.002) achieves the highest data rate, while a higher learning rate (LR = 0.1) results in the lowest performance. This suggests that smaller learning rates enhance the model's efficiency in optimizing data rate.

## 4.3 Comparison of BER with Signal to Noise Ratio (SNR)

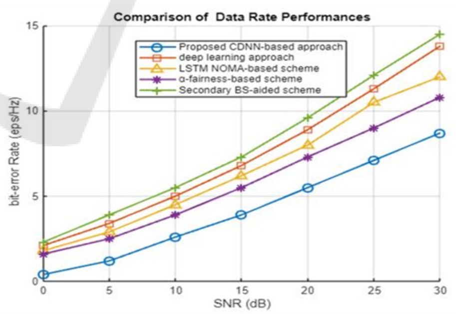


Figure 6: A Comparative Analysis of BER for Different Snr.

The Figure 6 compares the data rate performance of different approaches against SNR (dB) in terms of bit-error rate (eps/Hz). The proposed CDNN-based approach shows the lowest bit-error rate, indicating superior performance. Other methods, such as deep learning, LSTM-NOMA, αfairness, and Secondary BS-aided schemes, have higher error rates. This suggests that CDNN-based optimization is more efficient in improving data rate performance.

### 4.4 Comparison Energy Efficiency with SNR

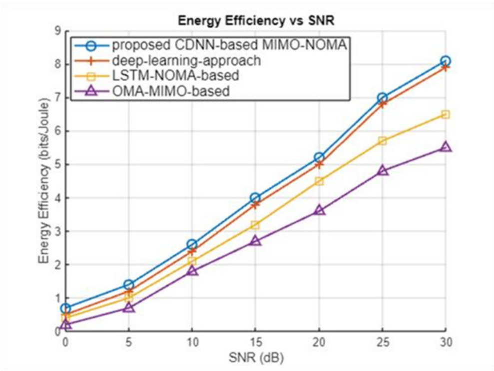


Figure 7: A Comparison of Energy Efficiency Versus Signal-To-Noise Ratio (SNR) Is Presented for the Proposed CDNN-Based MIMO-NOMA Scheme, the LSTM-NOMA Based Scheme, and the Conventional OMA-MIMO Based Scheme.

The Figure 7 compares energy efficiency (bits/Joule) versus SNR (dB) for different approaches. The proposed method (blue line) achieves the highest energy efficiency, followed closely by the deep-learning approach. NOMA based LSTM and MIMO-based OMA methods perform worse, with OMA-MIMO being the least efficient. This indicates that CDNN-based optimization enhances energy efficiency in wireless communication.

## 5 STATISTICAL ANALYSIS

Data obtained from parameters such as SNR (dB) for secondary BS-aided scheme, fairness-based scheme, LSTM-NOMA based scheme, deep learning scheme, and proposed CDNN scheme are analyzed using SPSS version 26.0 in Table 1. SPSS software is used to calculate the group statistics and the independent samples (Gui et al., n.d.). Independent variables for the study are the number of Schemes while SNR (dB)are dependent variables.

Table 1: Date Rate for Different Schemes.

| S. No | SNR (dB) | Data Rate (Bits/Hertz) | | | | |
|---|---|---|---|---|---|---|
| | | Secondary BS aided scheme | α-fairness based scheme | LSTM-NOMA based scheme | Deep learning approach | Proposed CDNN-based approach |
| 1 | 0 | 0.4 | 1.6 | 1.8 | 2.1 | 2.3 |
| 2 | 5 | 1.2 | 2.5 | 2.9 | 3.4 | 3.9 |
| 3 | 10 | 2.6 | 3.9 | 4.5 | 5 | 5.5 |
| 4 | 15 | 3.9 | 5.5 | 6.2 | 6.8 | 7.3 |
| 5 | 20 | 5.5 | 7.3 | 8 | 8.9 | 9.6 |
| 6 | 25 | 7.1 | 9 | 10.5 | 11.3 | 12.1 |
| 7 | 30 | 8.7 | 10.8 | 12 | 13.8 | 14.5 |

Table 2: T-Test Comparison Means Data Rate Improvement of Proposed CDNN Scheme Approaches Other Schemes.

| | Scheme | Mean | Std. Dev | Std. Error of Mean |
|---|---|---|---|---|
| Data rate | Secondary BS-aided scheme | 2.4586 | 0.32526 | 1.3433 |
| | α-fairness based scheme | 2.4986 | 0.35569 | 1.3444 |
| | LSTM-NOMA based scheme | 2.5343 | 0.38883 | 1.4696 |
| | Deep learning approach | 2.6571 | 0.41097 | 1.5533 |
| | Proposed CDNN based scheme | 2.8514 | 0.45481 | 1.7190 |

In Proposed CDNN based scheme the N is 7 and mean value is 2.8514 and Std. deviation is 0.45481 and the Std.error mean is 1. 7190.It shows that proposed CDNN has high data rate compared to another scheme. Table 2 shows the T-Test comparison means data rate improvement of proposed CDNN scheme approaches other schemes. Table 3 shows the Independent samples test. T-Test comparison of, secondary BS-aided scheme, LSTM-NOMA based

scheme, the fairness-based scheme and deep learning with proposed CDNN based scheme. ($p<0.05$).

Table 3: Independent samples test. T-Test comparison of, secondary BS-aided scheme, LSTM-NOMA based scheme, the fairness-based scheme and deep learning with proposed CDNN based scheme. ($p<0.05$).

| Scheme | Levene's Test F | Sig | t | df | Sig (2-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval (Lower) | 95% Confidence Interval (Upper) |
|---|---|---|---|---|---|---|---|---|---|
| Fairness based scheme | 0.313 | 0.586 | -1.617 | 12 | 0.032 | -0.35286 | 0.21823 | -0.82833 | 0.12262 |
| Equal variances not assumed | | | -1.617 | 11.341 | 0.033 | -0.35286 | 0.83141 | -0.83141 | 0.12570 |
| Secondary based scheme | 0.014 | 0.907 | -1.287 | 12 | 0.022 | -0.30286 | 0.23534 | -0.81562 | 0.20991 |
| Equal variances not assumed | | | -1.287 | 11.946 | 0.023 | -0.30286 | 0.23534 | -0.81588 | 0.21016 |
| LSTM-NOMA based scheme | 0.059 | 0.812 | -1.369 | 12 | 0.019 | -0.31714 | 0.23168 | -0.82194 | 0.18765 |
| Equal variances not assumed | | | -1.369 | 11.879 | 0.019 | -0.31714 | 0.23168 | -0.82251 | 0.18823 |
| Deep learning rate | 0.114 | 0.741 | -0.859 | 12 | 0.047 | -0.19429 | 0.22616 | -0.68705 | 0.29847 |
| Equal variances not assumed | | | -0.859 | 11.717 | 0.048 | -0.19429 | 0.22616 | -0.68837 | 0.29980 |

## 6 DISCUSSION

The proposed CDNN based scheme has better energy efficiency and data rate than the Secondary BS-aided scheme, fairness aided based scheme, NOMA based LSTM scheme, deep learning-based scheme. The corresponding changes in Std.error mean from 1.3433 to 1. 7190.The result obtained in the research are having a high data rate compared to previous studies.

In cellular networks, MIMO technology employs multiple antennas at the base station to enhance communication in both the uplink and downlink directions. The method increases the energy efficiency and enhanced spectral (Hoydis, ten Brink, and Debbah, n.d.). Through power domain multiplexing, the non-orthogonal multiple access enables several clients to share the similar frequency resources. (Saito et al., n.d.). That 6G won't be a straightforward examination of more reach at highrepeat gatherings, but it will rather be a mix of impending creative examples driven by empowering, essential organizations.6G will coordinate quantum technologies, and blockchain to make a secure, insightful, and sustainable worldwide organization (Saad et al. 2025).

By applying deep learning, the paper aims to improve key tasks such as signal detection, interference cancellation, and channel estimation, ultimately enhancing spectral efficiency and reducing bit error rates (BER) in NOMA systems (Gui et al., n.d.). Data rate per cluster of the proposed scheme for the learning rate is set as 0.002, 0.001, 0.01, 0.1 (Ali, Hossain,and Kim, n.d.).The calculation meets from any beginning stage, and it arrives at inside 1/2 rates per client for each result aspect from the aggregate limit after only one cycle. Sum Limit Estimation: Scopes inside 0.5 rates/client/yield aspect after one iteration. Convergence Rate: The calculation accomplishes 95% of the ideal limit inside 5 emphasis (Yu et al. 2025). Remote frameworks where the hubs work on batteries with the goal that energy utilization should be limited while fulfilling given throughput and postpone prerequisites are thought of. In this unique situation, the best regulation methodology to limit the complete energy utilization expected to send a given number of pieces is broken down (Cui et al. 2025).

# 7 CONCLUSIONS

To enhance energy efficiency and data rate of the MIMO- NOMA system using a communication deep neural network was designed. The proposed CDNN based scheme is better than the Secondary BS-aided scheme, fairness aided based scheme, NOMA based LSTM scheme, deep learning scheme. In Secondary BS-aided based scheme the data rate mean is 2.4586, fairness aided based scheme mean is 2.4986, LSTM-NOMA based scheme mean is 2.5343, deep learning scheme mean is 2.6571 and proposed CDNN scheme mean is 2.8514. For the secondary BS-aided scheme, the standard deviation is 0.32526; for the fairness-based scheme, it is 0.35569; for the LSTM-NOMA, it is 0.41097; for the deep learning approach, it is 0.41097; and for the proposed CDNN scheme, it represents 0.45481.

# 8 SCOPE FOR FUTURE WORKS

In future, our focus will be directed towards thoroughly analyzing and addressing security challenges to safeguard the system against potential threats. At the same time, we will work on enhancing system capacity to improve performance, scalability, and overall efficiency, ensuring that it meets current and future demands effectively.

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