# Performance Analysis of Cooperative Non-Orthogonal Multiple Access System Using Deep Learning Technique

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Abstract: Non-Orthogonal Multiple Access (NOMA) has emerged as a promising technique to enhance spectral efficiency in wireless communication systems. It allows users with varying channel conditions to share the same frequency band, enabling simultaneous transmission. Cooperative NOMA, an extension of NOMA, further elevates system performance by leveraging cooperative communication and exploiting spatial diversity. This study proposes a novel approach for evaluating the performance of cooperative NOMA systems utilizing deep learning techniques, specifically Convolutional Neural Networks (CNNs). Unlike conventional analytical methods, deep learning models excel in capturing intricate patterns and correlations in large-scale wireless communication systems, rendering them well-suited for performance analysis tasks. The suggested CNN-based framework is trained using simulated data derived from a cooperative NOMA system model. Inputs to the CNN encompass channel state information, power allocation parameters, and other pertinent system parameters, while the output entails achievable Outage Probability or Bit Error Rate predictions. By discerning the relationship between system parameters and performance metrics, the CNN adeptly forecasts the cooperative NOMA system's performance across diverse scenarios. The effectiveness of the proposed approach is assessed through extensive simulations, wherein the performance of the CNN-based model is juxtaposed against traditional analytical methods. Results indicate the CNN's superiority in terms of accuracy and computational efficiency, particularly in scenarios characterized by complex channel conditions and dynamic network environments. In summary, this study underscores the potential of deep learning techniques, particularly CNNs, in scrutinizing and optimizing cooperative NOMA systems. This paves the way for the streamlined design and deployment of next- generation wireless communication networks, promising enhanced efficiency and performance.

## 1 INTRODUCTION

Analyzing the performance of Cooperative Non-Orthogonal Multiple Access (CNOMA) systems, with a focus on outage probability and bit error rate (BER), through the novel utilization of deep learning techniques such as Convolutional Neural Networks (CNNs), represents a significant leap in wireless communication research (Dong, Chen, et al. , 2017). CNOMA, blending cooperative communication and Non- Orthogonal Multiple Access (NOMA) principles, holds immense potential for enhancing spectral efficiency and system reliability in wireless networks. In this study, our objective is to leverage CNNs to conduct an extensive exploration of CNOMA system performance (Sari, Gui, et al. , 2018).

Diverging from traditional analytical methods, which may fall short in capturing the intricate dynamics of large-scale wireless communication systems, deep learning models offer an appealing alternative by discerning complex patterns and correlations directly from data (Sari, Adachi, et al. , 2020). Our aim is to train CNNs using simulated datasets derived from CNOMA system models, aiming to develop robust predictive models adept at accurately estimating outage probability and BER across diverse operational scenarios. To achieve this goal, we follow a comprehensive research methodology. We meticulously construct a CNOMA system model, delineating parameters like user distributions, channel characteristics, power allocation strategies, and cooperative relay schemes (Gui, Song, et al. , 2018). Using simulation tools like



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MATLAB, we generate synthetic datasets spanning a wide spectrum of CNOMA system scenarios, encompassing variations in channel conditions, user densities, and system configurations (Huang, Guo, et al. , 2019), (Huang, Guo, et al. , 2019).

These synthetic datasets serve as the training data for our CNN-based predictive models. Input features fed into the CNNs include channel state information (CSI), power allocation parameters, cooperative relay details, and other relevant system attributes, while the desired performance metrics— outage probability and BER—serve as the output (Lu, Cheng, et al. , 2021).

During the training phase, standard deep learning techniques such as backpropagation and stochastic gradient descent are employed to fine-tune the CNN parameters, minimizing the gap between predicted and actual performance metrics on the training dataset. Techniques like cross-validation and regularization are utilized to ensure the generalization and robustness of the trained models. Subsequently, the performance of the CNN-based predictive models undergoes rigorous evaluation using separate validation datasets, assessing their accuracy and reliability in predicting outage probability and BER across a spectrum of CNOMA system scenarios. Comparative analyses with conventional analytical methods are conducted to validate the effectiveness and computational efficiency of the CNN-based approach. Through this comprehensive analysis, our research aims to provide profound insights into the behavior and optimization of CNOMA systems, particularly concerning outage probability and BER. The resultant CNN-based predictive models hold the potential to revolutionize the design and optimization of CNOMA-based wireless communication networks, ushering in an era of heightened spectral efficiency, reliability, and performance in future wireless systems.

# 2 OBJECTIVE

## 2.1 Comparison of Outage probability of NOMA and CNOMA system with and without deep learning.

When evaluating wireless communication reliability, it is crucial to include the outage probability, which represents the possibility of not meeting quality of service requirements. Systems like NOMA and CNOMA provide improved spectrum efficiency and fairness. Without deep learning, conventional algorithms have a major role in performance, which could result in less than ideal results. On the other hand, incorporating deep learning enables adaptable parameter changes depending on dynamic circumstances, enhancing resource distribution and interference control. Deep learning can, in general, dramatically lower the likelihood of an outage in both NOMA and CNOMA systems.

## 2.2 Comparison of Bit error rate of NOMA and CNOMA system with and without deep learning.

An important metric for assessing communication quality is the bit error rate, or BER. The goal of NOMA and CNOMA systems is to maximise dependability and spectrum efficiency. Performance is dependent on conventional methods in the absence of deep learning, which might not fully utilise system capabilities. Adaptive modulation, coding, and decoding are made possible by integrating deep learning, which enhances error detection and repair. In general, BER in both NOMA and CNOMA systems can be greatly reduced by utilising deep learning, improving system reliability overall.

# 3 BLOCK DIAGRAM

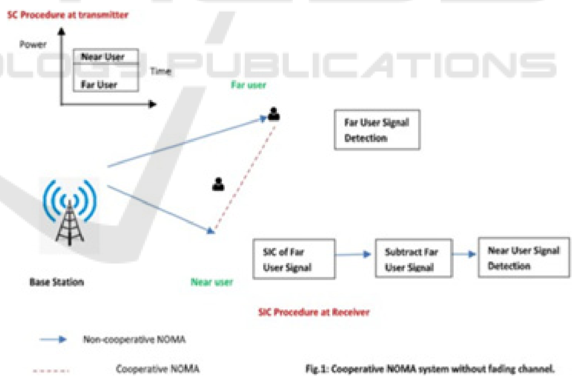


Figure 1: CNOMA System

The setup involves a single antenna utilized by both the source and users due to their significant distance from each other. In this configuration, besides serving as a direct transmission link between the source and both users, In addition, the Near user acts as a conduit for the Far user. Additionally, the Near user can harvest energy from the received signal by using the power splitting (PS) protocol compensating for energy loss during the relaying phase. The transmission process can be divided into cooperative and direct transmission phases. Signal detection for the Far User is achieved using a Successive Interference Cancellation (SIC) method based on Deep Learning (DL).

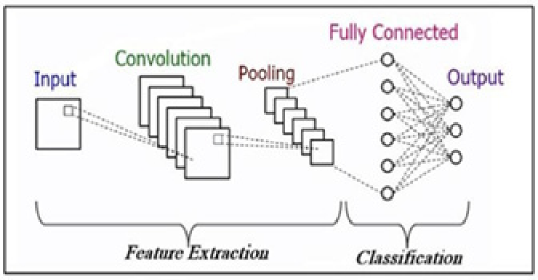


Figure 2: CNN Layers

A CNN model learns spatial feature hierarchies (e.g., horizontal, vertical lines) using the back propagation algorithm, leveraging building blocks such as fully linked layers, pooling layers, and convolutional layers. Typically, the CNN consists of the following layers: Convolutional Layer: The initial layer in the CNN, it consists of convolutional kernels (filters) where each neuron acts as a kernel. Convolutional pooling is utilized to process multiple inputs concurrently. Pooling Layer: Following the convolutional layer, this layer reduces the dimensionality of feature maps, extracting essential features while discarding irrelevant information. Fully Connected Layer (FC layer): Located at the end of the CNN, These layers serve as a link between each neuron in one layer and every other layer's neurons, facilitating complex pattern learning and accurate predictions

The CNN architecture generally features alternating convolution and pooling layers, often concluding with one or more FC layers. Convolutional layers play a key role in feature extraction, computing parameters like transmitted bits

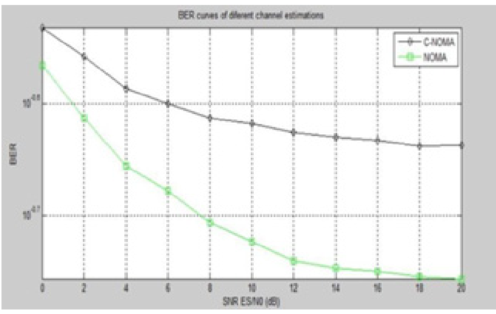


Figure 3: Graphical Analysis of BER for NOMA vs CNOMA:

and channel information. Ultimately, the classification phase enables precise recognition of transmitted data.

From Graphical analysis of horizontal green curve which indicates NOMA BER curve is below the Black curve which indicates CNOMA BER curve. From the graph different pairs of BER vs SNR values are tabulated and compared.

Table 1: Tabular Analysis of BER for NOMA vs CNOMA

| SNR(DB) | NOMA | CNOMA |
|---|---|---|
| 2 | 0.276 | 0.243 |
| 4 | 0.259 | 0.220 |
| 6 | 0.251 | 0.209 |
| 8 | 0.243 | 0.196 |
| 10 | 0.241 | 0.188 |

The above table determines the comparison of BER of NOMA and CNOMA systems for a given SNR values without using Deep Learning. From the table we can conclude that BER values of NOMA is higher than that of CNOMA . When the transmitted power is increasing down the column the BER values of both NOMA and CNOMA are decreasing.

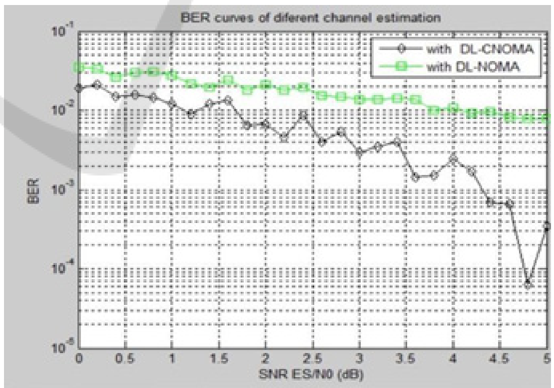


Figure 4: Graphical Analysis of BER for NOMA vs CNOMA with DL:

From Graphical analysis of horizontal green curve which indicates NOMA Ber curve is below the Black curve which indicates CNOMA Ber curve . From the graph different pairs of Ber vs SNR values are tabulated and compared.

Table 2: Tabular Analysis of BER for NOMA vs CNOMA Using DL:

| SNR(DB) | NOMA | CNOMA |
|---|---|---|
| 1 | 0.027 | 0.011 |
| 2 | 0.021 | 0.006 |
| 3 | 0.013 | 0.0028 |
| 4 | 0.010 | 0.0024 |
| 5 | 0.007 | 0.0004 |

The above table determines the comparison of BER of NOMA and CNOMA systems for a given SNR values using Deep Learning technique that is Convolutional Neural Network. From the table we can conclude that BER values of NOMA is higher than that of CNOMA. When the transmitted power is increasing down the column the BER values of both NOMA and CNOMA are decreasing.

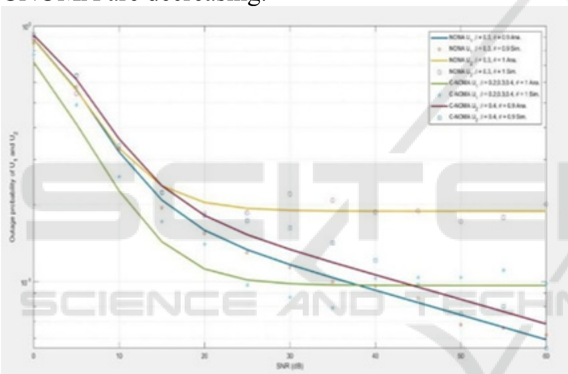

Figure 5: Outage Probability for NOMA vs CNOMA:

From Graphical analysis we have plotted the graphs of analytical and simulated outage probability values of both NOMA and CNOMA systems . Theta determines the available spectrum and beta determines required different frequency allocations. For different beta and theta values outage probability of Near and Far users of both the systems plotted and tabulated.

Table 3: Tabular Analysis of Outage Probability for NOMA vs CNOMA

| SNR(DB) | Near User (U1) | Far User(U2) | Near User(U1) | Far Use (U2) |
|---|---|---|---|---|
| 5 | 0.57 | 0.61 | 0.51 | 0.57 |
| 10 | 0.31 | 0.36 | 0.26 | 0.29 |
| 15 | 0.21 | 0.26 | 0.12 | 0.19 |
| 20 | 0.16 | 0.17 | 0.04 | 0.119 |
| 25 | 0.13 | 0.15 | 0.02 | 0.114 |

The above table indicates the comparison of outage probability of NOMA and CNOMA systems for a given SNR values without using Deep Learning technique. When we compare far and near users of both systems near user outage probability is lesser thanthe far user, but when we compare the near user of both the systems and far user of both the systems CNOMA's outage probability is lesser than NOMA due to the realy connection between the users.

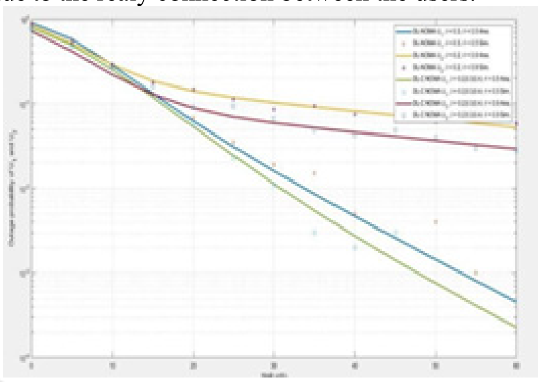

Figure 6: Outage Probability for NOMA vs CNOMA using Deep Learning:

From Graphical analysis we have plotted the graphs of analytical and simulated outage probability values of both NOMA and CNOMA systems . Theta determines the available spectrum and beta determines required different frequency allocations. For different beta and theta values outage probability of Near and Far users of both the systems plotted and tabulated.

Table 4: Tabular Analysis of Outage Probability for NOMA vs CNOMA using Deep Learning:

| SNR(DB) | Near User (U1) | Far User(U2) | Near User (U2) | Far User(U1 ) |
|---|---|---|---|---|
| 5 | 0.49 | 0.58 | 0.48 | 0.52 |
| 10 | 0.29 | 0.32 | 0.28 | 0.27 |
| 15 | 0.14 | 0.23 | 0.18 | 0.14 |
| 20 | 0.13 | 0.19 | 0.06 | 0.08 |
| 25 | 0.09 | 0.18 | 0.03 | 0.06 |

The above table indicates the comparison of outage probability of NOMA and CNOMA systems for a given SNR values using Deep Learning technique i.e Convolutiona Neural Network. When we compare far and near users of both systems near user outage probability is lesser than the far user, but when we compare the near user of both the systems and far user of both the systems CNOMA's outage probability is lesser than NOMA due to the relay connection between the two users in CNOMA system.

Therefore when we compare the values of outage probability of NOMA and CNOMA systems with and without Deep learning from both the tables we can conclude that the outage probabilities of both the systems is reduced from normal conventional SIC (Successive interference cancellation) to Deep Learning based SIC.

# 4 CONCLUSIONS

We have shown how cooperative NOMA systems execute performance analysis, using deep learning techniques to assess Bit Error Rate (BER) and Outage Probability. Our discoveries have provided important new information on the potential and capabilities of these kinds of systems. First off, our findings show that cooperative NOMA has significant performance advantages over conventional orthogonal multiple access systems in terms of BER and outage probability.

NOMA improves spectrum efficiency and reliability through effective power allocation and user grouping, especially in situations with a high user density and a variety of channel circumstances.

Second, there are encouraging outcomes when deep learning methods are combined with outage probability estimation and BER. When compared to traditional analytical techniques, convolutional neural networks (CNNs), a deep learning model, provide higher accuracy and robustness in capturing complicated channel behaviours and predicting performance indicators. These models provide more precise and effective predictions by learning from large-scale datasets, which helps with resource allocation and system optimisation.

Furthermore, in order to maximise the performance advantages of deep learning- based approaches, our study emphasises the significance of appropriate model architecture design, training data selection, and optimisation methodologies. The models accuracy and generalisation abilities can be further improved by adjusting network settings, utilising transfer learning, and investigating innovative architectures customised to particular NOMA system features, particularly in dynamic and heterogeneous wireless environments.

# 5 FUTURE SCOPE

It is anticipated that the combination of deep learning techniques and cooperative NOMA systems will greatly advance the field of wireless communication research. Investigating cross-layer methods, multi-objective optimisation, and dynamic resource allocation has the potential to completely transform the fairness and efficiency of systems. Furthermore, extending deep learning frameworks to massive MIMO environments and heterogeneous networks presents opportunities to improve system capacity and spectral efficiency. In order to refine these systems for practical implementation and sustainable operation, real-world deployment efforts and an emphasis on robustness, security, and energy efficiency will be crucial. When combined, cooperative NOMA systems and deep learning signal a new direction in wireless communication research that should help address the demands of future connection.

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