A Comparative analysis of Deep Learning-Aided-NOMA and Multi Carrier-NOMA for 5G Networks and beyond

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Abstract— This paper presents a comprehensive comparative analysis of deep learning-aided NOMA and multi-carrier NOMA for 5G networks and beyond. We investigate the performance of both techniques in terms of bit error rate, transmit power, signal-to-noise ratio, achievable capacity, outage probability, and data rate in a MATLAB environment. Simulation results of two techniques were evaluated. Furthermore, a comparative analysis identifies that the DL-NOMA exhibits superior performance in terms of power consumption, outage probability, and bit error rate. The results show that DL-NOMA reduces power consumption by 23.4%, outage probability by 27.6%, and improves bit error rate by 56.4%.

Keywords— *NOMA, MC-NOMA, deep learning, 5G networks, simulation.*

I. Introduction

Non-orthogonal multiple access (NOMA) stands out as a promising approach strategy to increase spectral efficiency and support a large number of users in 5th generation (5G) wireless networks [1]. For the third-generation partnership project long-term evolution advanced (3GPP-LTE-A) networks, a draft version of the NOMA, multiuser superposition transmission (MUST) scheme, has been put forth. NOMA's fundamental concept is to employ successive interference cancellation (SIC) to harness inter-user interference (IUI) and to take advantage of the power domain for multiuser multiplexing. Unlike traditional orthogonal multiple access (OMA) systems, NOMA uses superposition coding with varying power levels to allow several users to transmit simultaneously on the same degrees of freedom (DOF). In the interim, sophisticated signal processing methods, such as SIC, can be used to recover the desired signals at the receiver by taking advantage of the received power differential. It has been demonstrated that, in contrast to traditional OMA systems, NOMA can significantly improve the system spectral efficiency. Consequently, NOMA can enhance system spectral efficiency, lower communication latency, and enable large connections [2]. The majority of previous studies concentrated on downlink NOMA systems.

Nonetheless, NOMA is a natural occurrence in uplink communications, where a receiving base station (BS) naturally superimposes electromagnetic waves with varying received powers. Additionally, BSs typically pay less for SIC decoding than do mobile users. In the uplink, the authors examined NOMA with OMA from the standpoint of spectral-power efficiency. A resource allocation mechanism based on the maximum likelihood (ML) receiver at the BS was most recently created by the authors. However, NOMA's ability to provide equitable resource distribution is another important quality. NOMA enables simultaneous service of customers with different channel conditions, unlike OMA systems that may momentarily cease service to users with weaker channel conditions [3]. For the purpose of giving users in an uplink NOMA system maximum-min fairness, a power allocation strategy was devised. A proportional fair scheduling strategy design for non-orthogonal multiplexed users was examined by the authors. Fairness considerations in power allocation were examined for NOMA downlink systems with one antenna and those with multiple antennae, respectively. It is currently unknown why and when NOMA provides a fairer resource allocation than OMA, even though several early studies have previously taken fairness in resource allocation into consideration [4]. [5]. The ability of NOMA to serve numerous users with the same time and frequency resources is the main justification for its adoption in 5G. The power-domain and code-domain are the two primary NOMA approaches. While code-domain NOMA accomplishes multiplexing in the coding domain, power-domain NOMA accomplishes multiplexing in the power domain. Power-domain NOMA (henceforth referred to as NOMA) is the subject of this essay [6] [7]. The secrecy issue of NOMA has been studied recently because of its many benefits. The difficulty of achieving secure communications with NOMA persists because relays retransmit a copy of the information symbols, which are combined through SC and sent over the same frequency band. This allows all user messages to be intercepted once the eavesdropper locates the carrier frequency. In NOMA cooperative relay networks, this is particularly true [8][9]. Uplink NOMA system power reduction research is still in its early stages, and more work is needed in this area. In order to achieve this, in this study we take into consideration the power minimization for a multi-cell uplink NOMA system. Because they enable spectrum-efficient and energy-efficient system designs, respectively, Multi-Carrier Non-Orthogonal Multiple Access (MC-NOMA) and Simultaneous Wireless Information and Power Transfer (SWIPT) are emerging as key technologies for future Fifth-Generation (5G) and beyond wireless networks. According to [10], multi-carrier non-orthogonal multiple access (MC-NOMA) and simultaneous wireless information and power transfer (SWIPT) are promising technologies for upcoming fifth-generation (5G) and beyond wireless networks because of their potential for spectrum-efficient and energy-efficient system designs, respectively.

Deep learning is a method in artificial intelligence (AI) that teaches computers to process data in a way that is inspired by the human brain. Deep learning models can recognize complex patterns in pictures, text, sounds, and other data to produce accurate insights and predictions. We can use deep learning methods to automate tasks that typically require human intelligence, such as describing images or transcribing a sound file into text.

Deep learning technology drives many AI applications used in everyday products, such as:

i- Digital assistants
ii-Voice-activated television remotes
iii- Fraud detection
iv- Automatic facial recognition

Deep learning algorithms are incredibly complex, and there are different types of neural networks to address specific problems or datasets. Here are six models of it:

i- Convolutional neural networks (CNNs or ConvNets) are used primarily in computer vision and image classification applications. They can detect features and patterns within images and videos, enabling tasks such as object detection, image recognition, pattern recognition, and face recognition.

ii- Recurrent neural networks (RNNs) are typically used in natural language and speech recognition applications, as they use sequential or time-series data. RNNs can be identified by their feedback loops.

iii- Generative adversarial networks (GANs) are neural networks that are used both in and outside of artificial intelligence (AI) to create new data resembling the original training data.

v- Diffusion models are generative models that are trained using the forward and reverse diffusion process of progressive noise-addition and denoising.

vi- Transformer models combine an encoder-decoder architecture with a text-processing mechanism and have revolutionized how language models are trained. An encoder converts raw, unannotated text into representations known as embeddings; the decoder takes these embeddings together with previous outputs of the model and successively predicts each word in a sentence. [11]

2. WORK RELATED

According to the author in [12], multi-carrier non-orthogonal multiple access (MC-NOMA) and simultaneous wireless information and power transfer (SWIPT) are promising technologies for fifth generation (5G) and beyond wireless networks because of their potential for energy-efficient and spectrum-efficient system designs, respectively. The joint downlink resource allocation problem for a SWIPT-enabled MC-NOMA system with time switching (TS)-based receivers is examined in this study using the pattern division multiple access (PDMA) technique. Our goal is to minimize the systems' overall transmit power while meeting each user's quality-of-service (QoS) demands for collected power and data rate. The corresponding optimization problem is a challenging mixed integer programming problem that is non-convex.

A multi-cell uplink non-orthogonal multiple access (NOMA) system with poor successive interference cancellation (SIC) is examined in the work in [13]. The optimization problem's goal is to reduce overall power usage while adhering to consumers' quality-of-service requirements. Prior to proposing centralized and distributed optimal solutions, the problem under consideration is first converted into a linear programming problem. To confirm the effectiveness of the suggested methods and assess how incomplete SIC affects system performance, numerical results are provided. Inter-cell and inner-cell interference resulted from the assumption of universal frequency reuse and incomplete SIC, respectively. Both centralized and distributed solutions were obtained when the defined problem was first converted to a linear programming problem. The numerical results indicate that NOMA with perfect SIC surpasses OMA in terms of both sum power consumption and outage probability. However, this advantage diminishes as the imperfect SIC coefficient β increases, eventually disappearing when β becomes sufficiently large. Furthermore, the proposed distributed solution achieves convergence to the optimal solution in only a few iterations, significantly reducing signaling overhead compared to the centralized approach.

In [14], the author explores and substantiates the NP-hard nature of a power optimization problem within non-orthogonal multiple access (NOMA) systems through mathematical formulation. To tackle the problem, the approach begins by relaxing the problem to derive a convex formulation. Building on this, the author introduces a viable "relax-then-adjust" strategy based on the identified convexity and shares insights from corresponding performance evaluations. The study delves into complexity analysis, algorithm design, and performance assessments associated with power minimization in NOMA systems. To broaden its scope, an expansion of the work could focus on integrating NOMA into scheduling along the temporal dimension, addressing metrics like overall latency while incorporating a mix of service types.

The study in [15] introduces a novel multi-carrier non-orthogonal multiple-access (MC-NOMA)-enhanced Wireless Federated Learning (WFL) framework, designed within an adaptive learning paradigm using Flexible aggregation. In this setup, each WFL round incorporates both local model training and uploading for individual users. Flexible Aggregation enables users to perform different numbers of training iterations per round, allowing adaptation to varying channel conditions and computational capabilities. The approach leverages MC-NOMA to support simultaneous uploads of users' local models, thus extending their local training time and accommodating more participants in the learning process. Additionally, a new analytical metric—Weighted Global Proportion of Trained Mini-batches

(WGPTM)—is formulated to evaluate the convergence behavior of this advanced system.
In this study [16], the researchers address multi-cell multi-carrier non-orthogonal multiple access (MCMC-NOMA) networks and explore the problem of energy efficiency (EE) maximization. Since the EE maximization challenge is classified as a mixed-integer nonlinear programming NP-hard problem, it cannot be effectively solved using traditional optimization methods such as convex optimization. To tackle this issue, the problem is divided into two sub-problems. The first focuses on user association, wherein a matching-based framework is developed to manage user association and subcarrier allocation. The second sub-problem addresses power allocation for each user to optimize the energy efficiency (EE) of the system. Given that the EE maximization problem remains non-convex in the power domain, a two-stage quadratic transformation is proposed. This transformation involves both a single-ratio quadratic and a multidimensional quadratic approach to reformulate the problem into an equivalent convex optimization framework. The power allocation solution is derived by iteratively solving this convex problem. Numerical results highlight that the proposed method achieves superior EE compared to existing approaches for non-orthogonal multiple access (NOMA) and significantly outperforms the fractional transmit power control (FTPC) scheme for orthogonal multiple access (OMA).

3. SYSTEM MODEL

A downlink communication connecting the two users and the base station (BS) has been contemplated. Figure.1 depicts the model system. Due to his distance from the transmitting BS, user-1 is the weakest and most distant. The near/strong user is user number two. Let and represent how far away they are from the BS. User-1 (distant user) and User-2 (near user) receive two different messages from the (BS). and are, respectively, the factors of power allocation for the near and remote users ($\alpha_1 + \alpha_2 = 1$). Greater power is granted to the distant user and with less control to the nearby user in (NOMA) in order to enhance user fairness. In other words, we shall utilize α_1 =0.75 and α_2 =0.25 in this post. This decision is arbitrary. Let h_1 and h_2 represent the channel from the BS to the distant and close user.

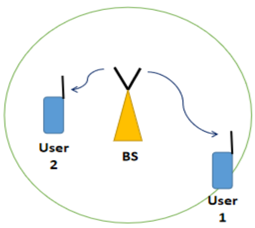

Figure 1: System Model.

Before calculating the final output, the network is shown the input and desired target in the deep learning technique seen in Figure 2. The error here is defining the discrepancy between the intended and actual results. The network will keep utilizing the error to modify the weights and biases for each neuron if the error exceeds the allowable threshold. However, this process of modifying weights and biases does not go on forever. Until the error achieves a satisfactory value (usually error $\leq$ goal), the network repeats the process, indicating that the NN was successfully trained. The NN training appears to have failed; it reaches the maximum number of iterations without meeting the desired objective.

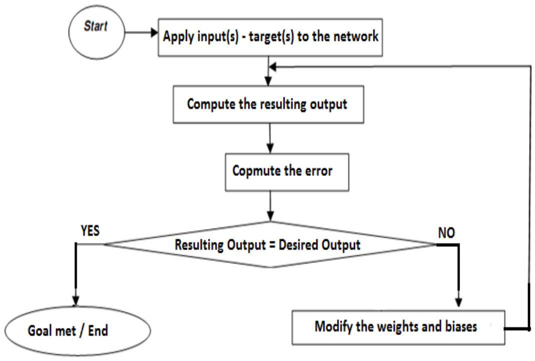

Figure 2. System Flow chart

The potential relationship between the input-data and output-data can be captured by this model, which belongs to the representative class of deep learning networks. The DBN's architecture design includes an input-layer, multiple hidden layers, and an output-layer, which is often described as a sequence of restriction Boltz-man Machines (RBMs), as seen in Figure 3. A visible-layer and a concealed-layer make up each RBM. Specifically, neurons within the same layer are disconnected, whereas neurons within the visible and hidden layers are fully coupled with a particular weight. Furthermore, the first RBM uses its initial hidden layer as its own Hidden-layer while accepting the DBN's input layer as its visible layer. In a similar manner, the second RBM utilizes the DBN's second hidden layer as its own hidden layer and uses the Hidden-layer of the previous RBM as its visible layer. There are two stages to the training process for every DBN. To roughly ascertain the DBN's parameters, the RBMs are trained individually using unsupervised learning in the first step. In the second stage, the back-propagation technique is used to fine-tune all of the DBN's parameters through supervised learning.

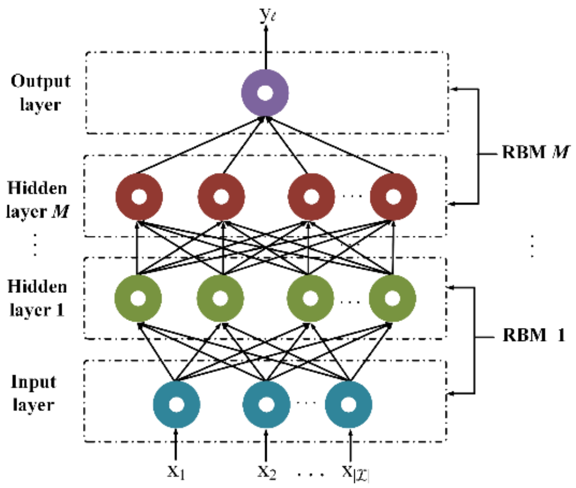

Figure 3: DBN framework used.

3. Performance metrics

The transmitted NOMA signal by the BS is given by:

$x = \sqrt{P}(\sqrt{\alpha_1}x_1 + \sqrt{\alpha_2}x_2)$ .... (1)

Whereas, P is the power transmit.

The copy of x received at the far-user after propagating through channel h_1 is,

$y_1 = h_1 x + w_1$ .... (2)

Similarly, the copy of x received at the near-user after propagating through channel h_2 is,

$y_2 = h_2 x + w_2$ .... (3)

NOMA decoding at User-1 (far-user)

Expanding the signal that was received at user-1,

$$y_1 = h_1 x + w_1$$
$$= h_1\sqrt{P}(\sqrt{\alpha_1}x_1 + \sqrt{\alpha_2}x_2) + w_1$$
$$= \underbrace{h_1\sqrt{P}\sqrt{\alpha_1}x_1}_{desired\ and\ dominating} + \underbrace{h_1\sqrt{P}\sqrt{\alpha_2}x_2}_{Interference} + \underbrace{w_1}_{Noise} \quad \text{........... (4)}$$

Since $\alpha_1 > \alpha_2$, direct decoding of y_1 result in x_1, where the term containing the x_2 component is considered interference. The signal-to-interference-and-noise ratio (SINR) for the far-user is calculated as follows:

$$\gamma_1 = \frac{|h_1|^2 P\alpha_1}{|h_1|^2 P\alpha_2 + \sigma^2} \quad \text{............................. (5)}$$

and the data rate he can achieved is,

$$R_1 = (1 + \gamma_1) = \ log_2(1 + \frac{|h_1|^2 P\alpha_1}{|h_1|^2 P\alpha_2 + \sigma^2}) \quad \text{........... (6)}$$

NOMA decoding at User-2 (near-user)

$$y_2 = h_2 x + w_2$$
$$= h_2\sqrt{P}(\sqrt{\alpha_1}x_1 + \sqrt{\alpha_2}x_2) + w_2$$

$$= \underbrace{h_2\sqrt{P}\sqrt{\alpha_1}x_1}_{desired\ and\ dominating} + \underbrace{h_2\sqrt{P}\sqrt{\alpha_2}x_2}_{Interference} + \underbrace{w_2}_{Noise} \text{...... (7)}$$

User-2 is required to execute Successive Interference Cancellation (SIC) prior to decoding their own signal. The SIC process proceeds as follows:

y_2 is directly decoded to produce x_1 or, more accurately, an approximation of x_1, denoted as $\widetilde{x_1}$.

$\widetilde{y_2} = y_2 - \sqrt{\alpha_1}\widetilde{x_1}$ is computed.

A perfect SIC assumption here has been made.

The signal-to-interference-and-noise ratio at the user-2 for decoding the user-1 signal (prior SIC) is,

$$\gamma_{1,2} = \frac{|h_2|^2 P\alpha_1}{|h_2|^2 P\alpha_2 + \sigma^2} \quad \text{............................ (8)}$$

The corresponding achievable data rate is

$$R_{1,2} = (1 + \gamma_{1,2}) = \ log_2(1 + \frac{|h_2|^2 P\alpha_1}{|h_2|^2 P\alpha_2 + \sigma^2})$$
.... (9)

After cancelled out of user-1's signal via SIC, the signal-to-noise ratio at the user-2 for decoding its own signal is,

$$\gamma_2 = \frac{|h_2|^2 P\alpha_2}{\sigma^2} \quad \text{.............................. (10)}$$

The corresponding data rate that can be achieved is

$$R_2 = (1 + \gamma_2) = \ log_2(1 + \frac{|h_2|^2 P\alpha_2}{\sigma^2}) \text{...... (11)}$$

4. Simulation Description

The mathematical details of MC-NOMA are presented above and now the simulation using MATLAB is considered. There are two scenarios. One is to study the BER performance, while another is to study the capacity and outage performance of MC-NOMA. initially, a few parameters' values are defined. Assume that the distances are, d_1=1000 meters and d_2 = 500 meters and the factors of power allocation as α1=0.75 and α2=0.25, after that a transmit power range from 0 dBm to 40 dBm has been initialized. The system bandwidth is set as B=600 MHz and the thermal noise power as $N_o = KTB$ where k=1.38× 10^{-23} J/K T=300 K has been calculated. Next, the Rayleigh fading coefficients h_1 and h_2 has been generated to simulate the channel between the two users. Then the resulting curve has been plotted, and the average value of each of the mentioned quantities has been calculated for every transmission power across various levels of power (e.g from 0 to 40 dBm). The first step is to generate noise samples for both users and random binary data for both users. In the code given here, BPSK is used for each user. The superposition coded signal x is calculated and equalized y_1 and y_2 by diving by h_1 and h_2 respectively. From the equalized version of $y_1$perform direct BPSK demodulation to obtain $\widetilde{x_1}$. Then compare $\widetilde{x_1}$ with user 1's original data to estimate BER using the biterr function. Finally, directly decode the equalized version of y_2 to estimate x_1. After multiplying the remodulated x_1 component by $\sqrt{\alpha_1}$, subtract it from the equalized version of y_2 . To obtain x_2 decode this signal. Use the biter function to estimate BER after comparing x_2 with user 2's original data and estimate BER using the biterr function.

Plot the BERs against transmit power.

The moment at which the power received (P_r) falls below a certain threshold (P_{min}) is known as the outage probability. Figure.4 illustrates the outage probability under two scenarios: a) path loss only, which produces a deterministic model; gives a deterministic model, and b) path loss and shadowing, which results in a continuous system.

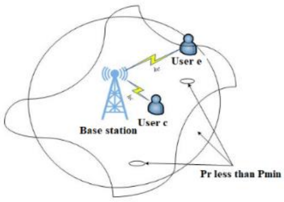

Figure 4. a: Outage Probability with Path Loss only,

In Figure 4-a, the power degradation is equal to the power received in the circle as users get farther away from the transmitter. There are no outages and no possibility of one when a certain threshold is reached. The likelihood of experiencing an outage is one once the barrier is crossed. Certain parts of the cell are also experiencing an outage, as indicated by the shadowing in Figure 4-b, when the received power is below the threshold.

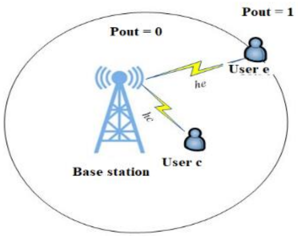

Figure 4: b. Outage Probability Path loss and Shadowing

Table1 shows the simulation parameters; here the impact on the system is demonstrated by varying the number of users from 10 to 200. The number of antennas varies from 5 to 60, and the bandwidth is set to 1 GHz. The maximum power is 46 dBm, and the power consumption is 30 dBm; a circular coverage with radii of 500 meters is assumed for the system.

Table 1. Simulation Parameters

Parameter	Value
BS maximum transmit power	46 dBm
Circuit power consumption	30 dBm
Coverage of BS	500-meter-radius circle
Bandwidth for wireless (BW)	1 GH
Users' number (k)	{5, 10, 15, . . ., 60}
Model of distribution for users	Equal distribution
Umax in NOMA	{2, 4, 6}
Users' minimum distance from BS	20 m
Path loss based on distance	128.1 + 37.6 log10 (d) dB, where d is in Km
Fading on a small-scale	Fading of Rayleigh flats
Power density of AWGN	-174 dBm/Hz
Minimum rate required by each user	{0.25, 0.5, 0.75, 1, … , 5} Mbps

5. Results and Discussion

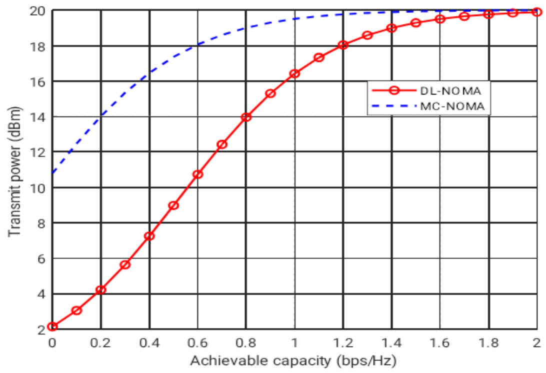

Figure 5: DL-NOMA power vs. MC-NOMA power

Figure 5, shows the capacity of MC-NOMA system. The figure compares the power for DL-NOMA and that for MC-NOMA.

For achievable capacity range, the average transmitted power of the proposed system is 13.86 dBm, while the traditional system has an average power of 18.1 dBm. The achievable minimization for the proposed system is 23.4 %.

Table 2. DL-NOMA power reduction

MC-NOMA Power	DL-NOMA Power	Reductio n
18.1	13.86	23.4 %.

Figure 6, shows the result of outage probability of the system for DL-NOMA and MC-NOMA. The equation of this result is represented in system model above. The outage probability ranges from 95.1% to 0.03% for the proposed DL system with average value of 19.6%, while it ranges between 99.9 % to 0.082 % with average value of 29.8% for the MC-NOMA, the enhancement in the outage probability is 27.6%.

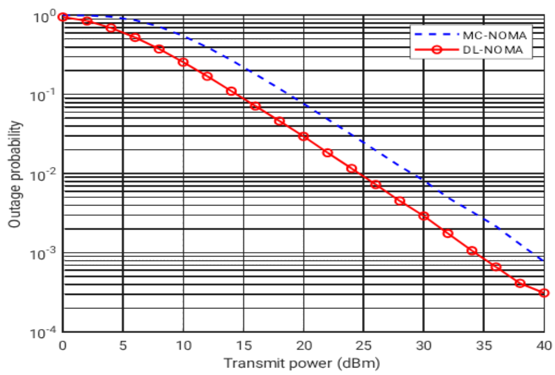

Figure 6: Comparison of outage probability for DL-NOMA and MC-NOMA

The Table 3 below shows a comparison between proposed system and traditional system, and shows the result of the comparison.

Table.3. Outage probability comparison

MC-NOMA Outage probability	DL-NOMA Outage probability	Reduction
29.8%	19.6%	27.6%

Figure.7 gives the BER vs. transmitted power, the dot-line is for traditional MC-NOMA and the other line is for proposed DL-NOMA system.

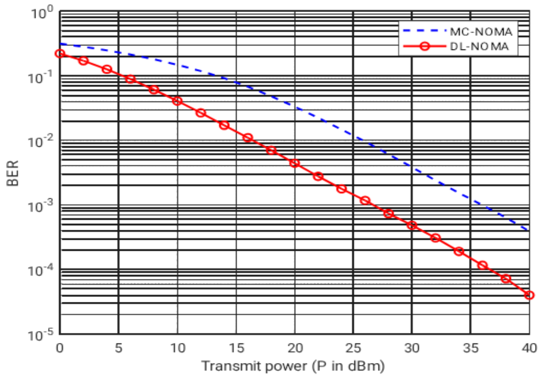

Figure 7: BER comparison for DL-NOMA and MC-NOMA

For the same level of power, it's clear that the DL system has a BER range between 0.0.221 to 0.000044 with an average value of 0.037, while the tradition MC-NOMA has a BER range between 0.314 up to 0.00042 with a mean of 0.086.

Table 4. BER comparison

DL-NOMA BER	MC-NOMA BER	Reduction
0.037	0.086	56.4 %.

Figure 8 shows the BER vs. SNR results for both systems, the proposed DL system has an average BER of 0.053, while the MC-NOMA system has an average BER of 0.11, the enhancement in the BER is 51%.

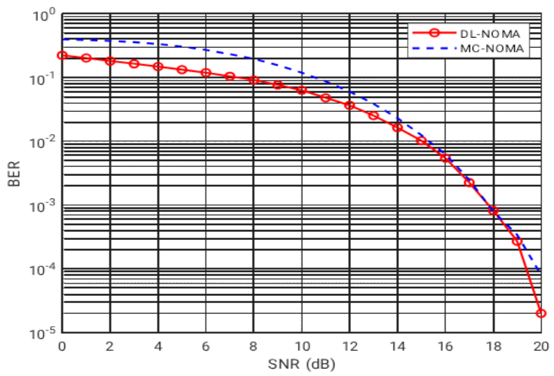

Figure 8: BER vs. SNR for MC-NOMA and DL-NOMA

The chart below assesses how well the minimum total power transmits required performs under different system settings. For comparison, each sub-carrier's noise power is set at 0.001/0.01/0.1 W. like the figure depicts. As the number of UEs increases under the same noisy power level, the deep learning-based method's lowest predicted total power transmission rises.

Furthermore, regardless of the number of UEs, the power transmit usage constantly rises as the noise power does. Specifically, the correlation between the UEs's number and the minimum transmit power may be roughly represented as a linear function, and its slope will rise as the noise power increases.

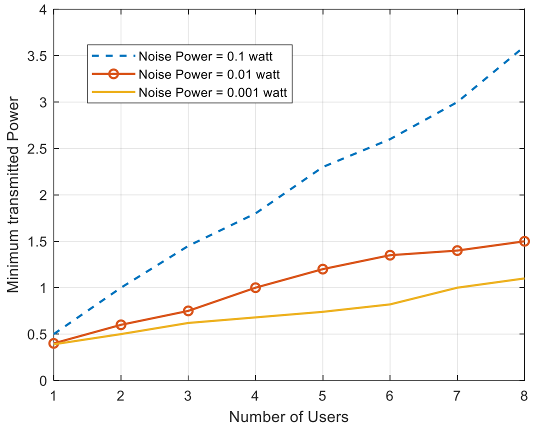

Figure 9 Power comparison for different noise power values

The minimum power need is set to vary from 0.02 W to 0.2 W, and the minimum rate of data required per user is set to vary from 0.2 Mbit/s to 2Mbit/s. Additionally, it is assumed that the noise power is σ 2 n = 0.01 W and the number of subcarriers is N = 4. For comparison, it is assumed that there are 3/4/5 UEs.

Figure 10 shows the increase in the total power transmitted due to the rise in the minimum rate of data, and this trend becomes more noticeable as the number of UEs rises.

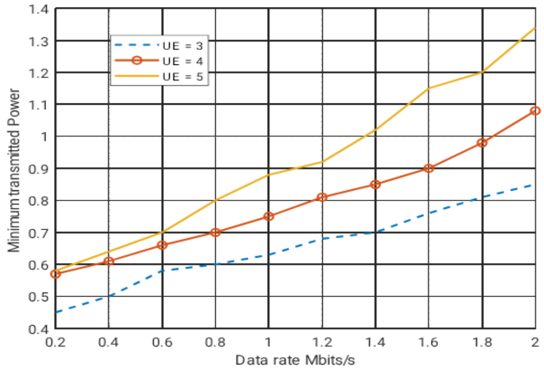

Figure 10: Transmitted power vs. data rate

Figure 11 shows that, the total transmit power increases with the amount of minimal requirement of collected power. The success of the suggested deep learning-based method is confirmed and validated by the findings.

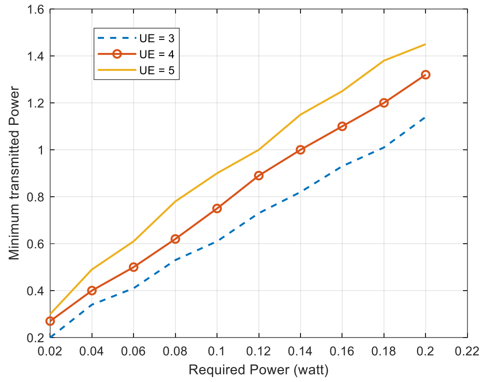

Figure 11: Total transmit power vs. harvested power

6. CONCLUSION

Multi-Carrier Non-Orthogonal Multiple Access (MCNOMA) is a promising technology for the next 5th generation (5G) and in addition to wireless networks due to the requirement designs for an efficient and energy-and-spectrum-efficient system.

The power minimization issue for an MC-NOMA system is examined in this paper. Our objective is to decrease the system overall power transmission while meeting the Bit Error Rate (BER) and harvesting power requirements of each user for Quality-of-Service (QoS).

The relevant optimization problem is a mixed integer programming problem that is non-convex and difficult to solve. We suggest an effective deep learning-based method to find an approximated optimal solution, which differs from the traditional iterative searching-based approaches. In particular, we use deep networks (DL), a common class of deep learning models, whose precise process is divided into three stages: preparation of data, training, and running. The outcomes of the simulation show that the suggested DL-based method can outperform the conventional MC-NOMA in terms of power usage. For the suggested system, a power minimization of 23.4% is feasible. Additionally, the suggested solution has improved BER by 56.4% and decreased outage probability by 27.6%. In order to compare the suggested system for varying numbers of users, another scenario is also provided. Three, four, and five users have all been used, and the outcome shows that the power increases as the number of users increases.

Authors' Contributions

Author's contributions:

First author: Research design, data collection, result analysis. Second author: Writing the article, reviewing the manuscript. All authors contributed to the discussion and approved the final version

Conflict of Interest

The authors declare that there is no conflict of interest.

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