International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Maximizing Deep Learning-Based Energy Efficiency in 5G Downlink MIMO-NOMA Systems by Using MLP-CNN

Kamil Audah*[1], Walaa Hussein[2], Nor Kamariah Noordin[3], Aduwati Sali [4], Mohd Fadlee A.Rasid[5]

Submitted: 27/01/2024 **Revised**: 05/03/2024 **Accepted**: 13/03/2024

Abstract: Multiple input multiple outputs-Nonorthogonal multiple access (MIMO-NOMA), presenting a potential technology to improve system performance and energy efficiency. Nevertheless, the system's effectiveness is hampered by the impact of swiftly changing channel conditions and intricate spatial structures, restricting its broader applicability. Deep learning plays a crucial role by helping MIMO-NOMA overcome challenges, improve Energy efficiency, and increase capacity and overall system performance in wireless communication networks. This research paper proposes a deep learning-based Multilayer Perceptron-Convolution neural network (MLP-CNN) framework. The framework optimizes the data rate and energy efficiency by addressing the power allocation problems. It can be utilized with multiple convolutional and hidden layers, trained using specific algorithms to solve power allocation problems. Simulation results demonstrate that the proposed framework improves power allocation, overall data rates, and Energy efficiency by around 15% compared to traditional deep neural network (DNN) algorithms, methods and strategies.

Keywords: *Energy Efficiency, 5G, MIMO-NOMA, Deep Learning, MLP-CNN*

1. Introduction

Nonorthogonal multiple access (NOMA) method is presented as a tool to optimize the utilization of the available spectrum for a more extensive user with varying power levels [1] in 5G systems, an approach that involves assigning greater transmission power to users experiencing relatively poor channels [2]. This strategy aims to balance system capacity and user fairness within a single cell served by a base station [3]. The term for this is power domain multiple access in the broadcasting region. The NOMA technique implements superposition coding, and in the receiving area, Signal to Interference Cancellation (SIC) allows users to share available resources [4]. Its purpose is to simultaneously transmit multiple messages by encoding them into single layers and scheduling them over the same transmission period and frequency range [5].

Conversely, at the receiving end, Signal to interference cancellation manages user information [6]. In this procedure, users with more substantial channel gains retrieve information from users with weaker channel gains. As a result, intra-cluster interference and co-channel interference are efficiently mitigated [7]. However, there are various challenges to the successful implementation of NOMA. Its necessarily faces such challenges that require a significantly higher rate of computational Power to execute multiple algorithms, especially in situations with more traffic at high data rates [8]. The optimization of Power in NOMA poses challenges, especially when user equipment is relocated within the network. The signal at the receiving end becomes more susceptible to errors, including potential cancellations [9]. Therefore, NOMA must be implemented using specific techniques, such as Multiple input multiple outputs (MIMO) or a coding scheme [10], to increase consistency and reduce decoding errors. MIMO has the advantage of providing additional degrees of freedom when applied to NOMA; hence, a MIMO-based NOMA system is discussed in this work [11]. The applications of Multiple input multiple outputs-Nonorthogonal multiple access (MIMO-NOMA) have attracted great interest because MIMO provides excellent flexibility for the improvement of performance [12]. Moreover, MIMO-NOMA stands out as a promising option to boost spectral efficiency further and minimize communication transmission delays. It has garnered significant interest for its potential performance improvements, leading to the proposal of various schemes based on MIMO-NOMA [13].

To increase spectrum and energy efficiency, the author presents millimetre-wave (mmWave) transmission, a new technology that combines the NOMA approach with beamspace MIMO. To mitigate inter-cell interference and enhance throughputs for cell-edge users, investigated a downlink multi-cell MIMO-NOMA system, optimizing coordinated beamforming methods using interference alignment jointly at two base stations. In a related context, the authors introduced user clustering for a mm-wave NOMA system, restricting NOMA application to users within the same cluster, while MIMO detection handled inter-cluster interference [14].

An effective MIMO-NOMA strategy involves designing

[1,2,3,4,5]Department of Computer and Communications Systems Engineering, University Putra Malaysia, 43400 UPM Serdang Selangor Darul Ehsan, Malaysia.
[1,2,3,4,5]Wireless and Photonic Networks Research Centre of Excellence (WiPNET), Faculty of Engineering and Technology, Universiti Putra Malaysia (UPM), Serdang,
** Corresponding Author Email: GS60037@student.upm.edu.my*

precoders and equalizers jointly, exhibiting superior power consumption to orthogonal multiple access (OMA) and signal alignment NOMA. Theoretical analyses show that in the 4G context, MIMO-NOMA systems offer higher capacity and data rates than multiple input multiple outputs-orthogonal multiple access (MIMO-OMA). Previous research explored power allocation strategies, with investigating sum data rates in a downlink MIMO-NOMA system [15]. The power-splitting method in MIMO-NOMA achieves lower power consumption for any arbitrarily chosen rate pair compared to MIMO-OMA [16]. A security model-based opportunistic NOMA framework was proposed to enhance network throughput and security in MIMO-NOMA, assigning distinct security levels to the base station and users. Additionally, [17] introduced a resource allocation approach, sequentially addressing Power and sub-carrier allocation, significantly improving spectrum and power efficiency in MIMO-NOMA. Moreover, by harnessing the MIMO-NOMA system, [18] proposed a dynamic arrangement of receive antennas at users into multiple clusters. The authors developed power allocation solutions to optimize the overall cell capacity, subject to the condition that the number of clusters should not surpass the number of transmit antennas at the base station. SIC requires precise Channel State Information (CSI) for each user, and the effectiveness of MIMO heavily relies on the accuracy of CSI. Existing power allocation methods hinge on perfect channel, but obtaining accurate channel in MIMO-NOMA systems poses significant challenges due to their inherently complex nature. The effectiveness of current power allocation strategies has diminished, emphasizing the importance of sparse information for channel estimation and precoding in MIMO. Power allocation challenges in MIMO-NOMA, aimed at maximizing data rates, with previous methods offering suboptimal solutions. While deep learning in wireless communication is relatively new, promising studies have shown improvements in traffic control systems, predicting traffic load, and addressing resource allocation challenges in unmanned aircraft systems compared to ground stations in dynamic situations.

This study presents extensive investigations and introduces a deep learning-driven framework to optimize MIMO-NOMA systems' total data rate and energy efficiency. The aim is to integrate deep learning algorithms seamlessly into MIMO-NOMA configurations to achieve optimal power allocation and enhance energy efficiency. The introduced framework ensures comprehensive performance optimization from end to end. To summarize, the main contributions of this paper are as follows:

- In this article, an effective deep learning algorithm is developed, combining a multilayer perceptron with a convolutional neural network to model the MIMO-NOMA system. This research employs specific activation functions across meticulously designed hidden and convolutional layers. Furthermore, the proposed framework introduces an efficient power allocation approach to enhance energy efficiency performance.
- This paper proposes a new dataset based on the MATLAB 5G simulator, which considers a MIMO-NOMA scenario between transmitter and receiver. A new dataset should contain a channel vector, precoding matrix, and power allocation factor based on the proposed scenario. These parameters should be inputted to the neural network.
- Comprehensive performance analyses are conducted to assess the effectiveness of the proposed Multilayer Perceptron-Convolution neural network (MLP-CNN) framework in terms of Power and energy efficiency. The results demonstrate that the proposed framework surpasses existing schemes, providing compelling evidence for the efficacy of the deep learning-based MIMO-NOMA system.

The subsequent sections of this paper are structured as follows: Section II outlines the development of a standard MIMO-NOMA system. Section III formulates the power allocation problem and introduces a deep neural network (DNN) framework to address its high complexity. Additionally, the authors detail a DNN-based method for enhancing the performance of MIMO-NOMA in terms of Power and energy efficiency. Section IV presents simulation results, while Section V provides analysis. Finally, Section VI concludes the paper.

2. Related Work

If The use of structured MIMO-NOMA systems proves beneficial in improving energy efficiency. The technology facilitates non-orthogonal sharing of time-frequency resources among multiple users, leading to increased energy efficiency and enhanced system capacity compared to conventional OMA schemes. This section will discuss related works that utilize MIMO and NOMA communication systems to improve energy efficiency and sum data rate. A new approach aims to maximize the reward signal to optimize the data rates for individual users. The study evaluates various metrics such as energy efficiency, minimum data, and sum rates by varying batch sizes and learning rates [19]. The results indicate that a batch size of 40 and a learning rate 0.001 yields the best performance. The proposed deep learning-based algorithm performs better than non-deep learning methods across all test scenarios [20]. Deep Learning methods introduce a power allocation strategy to maximize the cumulative system rate in a downlink MIMO-NOMA setup featuring imperfect SIC. An effective detection algorithm is employed to identify the optimal power, a power allocation approach is suggested to improve the overall system rate. The proposed technique leverages deep learning and exhaustive search to anticipate the optimal factors for power allocation.

The study of [21] tackles the challenging non-convex optimization of power allocation in mmWave NOMA systems, aiming to maximize the sum rate while adhering to power constraints and individual user quality of service requirements. An online k-means deep learning protocol is proposed for dynamic user grouping, managing computational complexity in environments with growing users. The research article [22] introduces federated learning within a NOMA framework to optimize energy efficiency and sum rate. It decentralizes data while training a model centrally, benefiting bandwidth-constrained wireless communication systems. Graph theory addresses power allocation optimization, incorporating NOMA to enhance accuracy and reduce communication latency in the downlink/uplink scenario involving one parameter server and multiple users. The review [23] analyses the evolution and significance of deep learning assisted communication, comparing it to MIMO, NOMA, and mmWave technologies. It addresses challenges, opportunities, and research directions in deep learning, emphasizing improved spectral efficiency, system capacity, and channel state estimation in deep learning-assisted NOMA systems. The study evaluates deep learning performance in mmWave communication, focusing on ultra-high-power consumption and limited link gains in deep learning-aided MIMO systems. However, it lacks a detailed discussion of energy efficiency challenges. The authors of [24] discuss NOMA's role in communication systems, detailing advantages and integrations, but fall short of thoroughly addressing energy models, power consumption aspects, open research challenges, and future directions for further investigations. The author examines downlink NOMA in a k-user multi-cell network, focusing on scenarios with two users in a single cell. The paper explores NOMA fundamentals, emphasizing its contributions to energy efficiency. Key aspects such as CSI, power allocation factors, and inter-channel interference are extensively covered. The analysis evaluates the potential and limitations of Machine Learning and Deep Learning in NOMA systems, aiming to clarify misconceptions about its efficacy in 5G and beyond. While addressing critical questions, the paper lacks an in-depth exploration of open research issues and future directions, suggesting a need for further investigation in subsequent studies [25].

As a result, this study successfully addresses various limitations and challenges by proposing a new efficient optimization technique that combines MLP with CNN integrated into the MIMO-NOMA system. The new method tackles power allocation and non-convex problems, improving overall system energy efficiency and data rate. Notably, the proposed approach demonstrates excellent performance based on training and validation results, as evidenced by minimum mean square error (MSE) and loss ratio metrics.

3. System Model

Use As depicted in Fig. 1, this investigation examines a standard downlink MIMO-NOMA configuration featuring a single base station equipped with a uniform linear array comprising number of base station antennas M and multi-antenna users D. The downlink channel is subject to Rayleigh fading. In this scenario, each user possesses number of receive antennas Nr, and it is assumed that the base station lacks information about the links of individual users. The users are randomly distributed into M clusters, each comprising number of users K. The multiplexing gain is capped at M when the number of antennas at the base station is M. In other words, M represents the maximum number of clusters that can be accommodated without encountering inter-cluster interference. Consequently, it can be serves as the critical parameter under investigation in this study. To make the complex problem of allocating beamforming vectors easier to understand., this paper assumes $Nr \geq M$. In the context of 5G wireless networks, small cells are anticipated to be deployed in an ultra-dense manner. Low-power and cost-effective small-cell base stations will be deployed. Consequently, it is reasonable to assume that such low-power base station may be equipped with equal or even fewer antennas than user equipment.

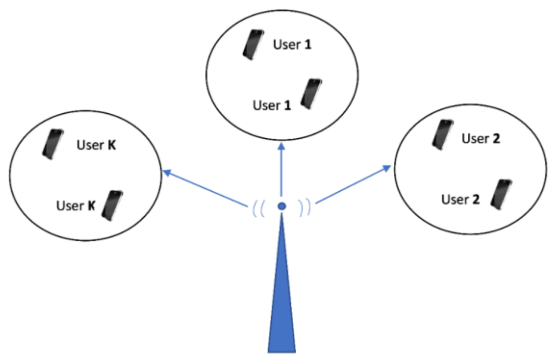

Fig. 1. Proposed MIMO-NOMA System Model.

This leads to the expression of the transmitted signal from the base station as follows:

$$x = Ps\,, \tag{1}$$

Suppose that P is the precoding matrix $M \times M$, and s can be formulated as:

$$s = \begin{bmatrix} \beta_{1,1}s_{1,1} + \cdots + \beta_{1,K}s_{1,K} \\ \vdots \\ \beta_{M,1}s_{M,1} + \cdots + \beta_{M,K}s_{M,K} \end{bmatrix} \square \begin{bmatrix} \overline{s_1} \\ \vdots \\ \overline{s_M} \end{bmatrix}, \tag{2}$$

Here, $s_{m,k} \sim \mathcal{CN}(0, \epsilon)$ is the signal carrying information transmitted to the k-th user in the m-th cluster, in which ε is the transmit Power per symbol. Where the power allocation coefficient for NOMA is denoted by $\beta_{i,j}$. If we suppose that the channel matrix $H_{m,k} \in \mathbb{C}^{N_r \times M}$ incorporating distance-dependent path loss effects for the k-th user in the m-th cluster. Specifically, concerning the initial cluster, the signal received by the k-th user is expressed as follows:

$$y_{1,k} = H_{1,k} Ps + z_{1,k} , \quad (3)$$

here $z \sim \mathcal{CN}(0, \sigma^2 I_{N_r})$ is Additive White Gaussian Noise (AWGN). This research can assume that the power allocation coefficients are arranged in a specific order without sacrificing any essential characteristics as $\beta_{1.1} \leq \beta_{1.2} \leq \cdots \leq \beta_{1.K}$, and the sequence of channel gains can be arranged as follows:

$$\left| v_{1,K}^H H_{1,K} p_1 \right|^2 \leq \left| v_{1,K-1}^H H_{1,K-1} p_1 \right|^2 \leq \cdots \leq \left| v_{1,1}^H H_{1,1} p_1 \right|^2 \quad (4)$$

In this context, $v_{1,K}$ the detection vector corresponds to the k-th user, here k-th user and p_i Represents the $i-th$ column of the precoding matrix P. In the context of MIMO-NOMA, the conventional maximum ratio combining detection vector is consistently employed to leverage the degrees of freedom inherent in the MIMO system. With careful design of the detection and precoding matrices, optimal solutions can be attained through SIC, as the MIMO-NOMA system can be simplified to the single input single output channel. Assuming P is fixed, the detection vector needs to adhere to the following constraint:

$$v_{1,k}^H h_{m,1k} = 0 , \quad (5)$$

where $h_{m,1k}$ is the $m-th$ column of $H_{1,k}$ and then the detection vector at $k-th$ is $v_{1,k}$ can be obtained as:

$$v_{1,k} = U_{1,k} n_{1,k} , \quad (6)$$

In this context, $U_{1,k}$ encompasses all the left singular vectors of $\bar{H}_{1,k}$where $\bar{H}_{1,k} = [h_{2,1K}, h_{3,1k} \ldots\ h_{M,1k}]$ is a submatrix of $H_{1,k}$ obtained by removing one column with zero singular values [26]. Following the maximum ratio combining method, $n_{1,k}$ is a normalized vector expressed as:

$$n_{1,k} = \frac{U_{1,k}^H h_{1,1k}}{\left| U_{1,k}^H h_{1,1k} \right|} , \quad (7)$$

Utilizing the principle of signal to interference cancellation, users with superior channel conditions can decode the users with more favourable channel conditions can decode the messages of users experiencing less fortunate conditions and subsequently decode their messages. Conversely, users with less good channel conditions can only decode their information. The derivation of the signal to interference plus noise ratio for the primary user in the initial cluster is expressed as follows:

$$\gamma_{1,1}^1 = \frac{\left| v_{1,1}^H H_{1,1} p1 \right|^2 \beta_{1,1}^2}{\sum_{m=2}^M \left| v_{1,1}^H H_{1,1} p_m \right|^2 + \left| v_{1,1} \right|^2 \frac{1}{\eta}} , \quad (8)$$

Here, η denotes the signal to noise ratio (SNR) of the transmitted signal. Under the assumption of perfect SIC, the signal to interference plus noise ratio for the k-th user in the first cluster is calculated as follows:

$$\gamma_{1,1}^1 = \frac{\left| v_{1,k}^H H_{1,k} p1 \right|^2 \beta_{1,k}^2}{\sum_{n=1}^{k-1} \left| v_{1,k}^H H_{1,k} p_1 \right|^2 \beta_{1,n}^2 + \sum_{m=2}^M \left| v_{1,k}^H H_{1,k} p_m \right| + \left| v_{1,k} \right|^2 \frac{1}{\eta}} , \quad (9)$$

This study employs a MIMO-NOMA framework with deep learning techniques, including MLP-CNN, to enhance system performance. By extracting valuable features, these algorithms optimize power allocation, interference management, and data rate maximization. The deep learning-based framework adapts to diverse environmental conditions and channel characteristics, ensuring self-optimization and optimal performance in dynamic scenarios, which is essential for modern wireless communication systems.

4. Deep Learning-Based MIMO-NOMA Systems

This study integrates a convolutional neural network (CNN) into the MIMO-NOMA system for optimizing sum data rate and energy efficiency. The CNN, deployed at the base station, addresses power allocation optimization by learning from channel links and user characteristics. The training process ensures comprehensive coverage of user information and channel conditions. Advanced algorithms within the deep learning framework further optimize the sum data rate and enhance the energy efficiency of the MIMO-NOMA system.

4.1. Problem Formulation

This system aims to enhance the overall data rate while improving energy efficiency. To provide more detail, assess the data rate for the k-th user in the primary cluster using the subsequent expression:

$$R_{1,k} = \log_2 \left(1 + \gamma_{1,k}^k \right) , \quad (10)$$

Consequently, the data rates for users in the remaining clusters can be determined similarly. The achievable sum data rate for the MIMO-NOMA system can be expressed as follows:

$$R_{sum} = \sum_{m=1}^M \sum_{k=1}^K R_{m,k} , \quad (11)$$

The total data rate, represented as sum data rate R_{sum} is impacted by both the output precoder p_m and the power allocation coefficients $\{\beta_{m,k}\}$, Hence, formulate an optimization problem to address this issue, aiming to maximize the sum data rate:

$$\max_{pm,\beta_{i,j}} R_{sum} = \max_{pm,\beta_{i,j}} \sum_{m=1}^{M}\sum_{k=1}^{K} R_{m,k} \ ,$$

St C1:

$$\sum_{m=1}^{M} \| p_m \| \leq p_{tr}\, , \forall m\, ,$$

C2:

$$R_{m,k} \geq R_{\min}\, , \forall m, k,$$

C3

(12)

$$0 \leq \| p_m \| \leq p_{tr}\, , \forall m\, ,$$

C4:

$$0 \leq \beta_{m,k} \leq 1, \forall m, k\, ,$$

C5:

$$\sum_{m=1}^{M}\sum_{k=1}^{K} \beta_{m,k} = 1.$$

The term $R_{\min}$ signifies the minimum data rate assigned to each user in each cluster. Subsequently, the proposed CNN framework was applied to address the problem (9). In this context, C1 refers to the overall transmit power constraint, where p_{tr} stands for the maximum total transmit Power. Constraints C2 and C3 correspond to the minimum data rate, and minimum allocated Power, respectively. Moreover, the condition about the order of successive interference cancellation decoding is articulated as follows:

$$v_{m,k} = \begin{cases} 0, \left| v_{m,k}^{H} H_{m,k} \right|^{2} \leq \left| v_{m,k+1}^{H} H_{m,k+1} \right|^{2} \\ 1, otherwise \end{cases} ,$$

The equation states that the binary variable. The SIC decoding order constraint $v_{m,k}$ Determines whether the k-th user in the m-th cluster performs SIC or not. A value of "1" indicates signal, while "0" signifies no signal. It is important to note that the optimization problem (12) contains continuous and combinatorial variables, making it a non-convex problem. The brute-force search method is impractical due to its high complexity, rendering it unsuitable for solving the problem stated in equation (12). On the other hand, deep learning has demonstrated its potential to approximate complex problems by utilizing networks with sufficient neurons and hidden layers. Therefore, deep learning becomes an attractive approach to address the optimization problem mentioned in equation (12).

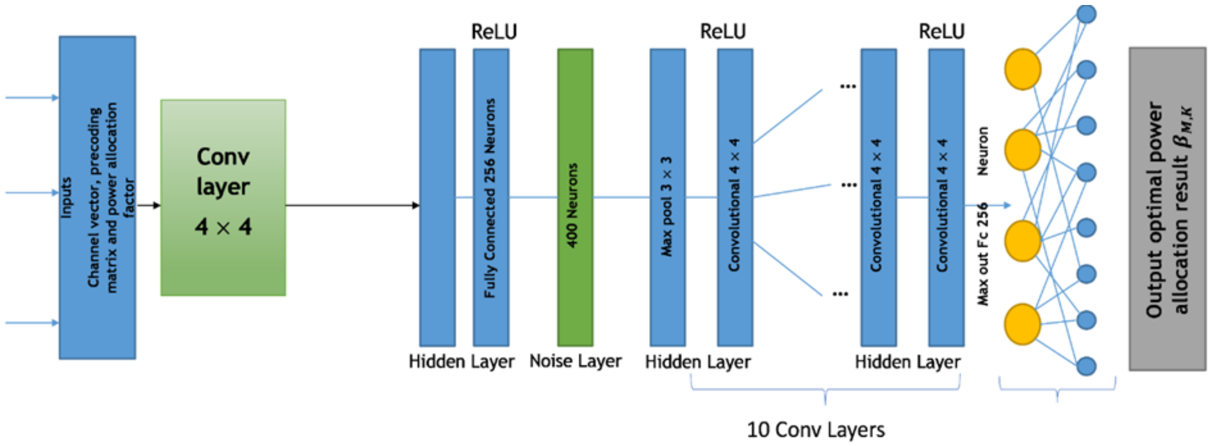

Fig. 2. MLP-CNN proposed framework.

4.2. Proposed Convolutional Neural Network Optimization Model

This section introduces an efficient optimization model named the MLP-CNN combination, leveraging the strengths of both models to enhance energy efficiency in MIMO-NOMA systems. Based on the universal approximation theorem, a DNN with multiple hidden layers is well-suited for capturing the statistics of MIMO-NOMA systems, addressing non-convex and nonlinear problems. The proposed combination utilizes the MLP technique to approximate continuous functions effectively and the robust CNN for complex channel estimation, which is particularly crucial for performing cancellation of signal in MIMO-NOMA systems.This research focuses on power allocation, a crucial aspect in advancing wireless communications and enhancing the energy efficiency of the MIMO-NOMA system. The model utilizes CSI matrices as inputs, acquired through pilot signal transmissions and channel estimation techniques. Convolutional layers capture spatial relationships akin to the CNN architecture. Flattened vectors pass through fully connected layers with varying sizes and activation functions. The model learns the relationship between CSI matrices and optimal power allocation coefficients, providing outputs for different users and groups. The CNN framework, involves multiple hidden layers with various neurons and common activation functions like Sigmoid and Rectified Linear Unit, which are represented by the following equations, respectively:

$$f_{sigmoid}\left(x\right)=\frac{1}{1+e^{-x}},\, f_{\mathrm{Re}LU}\left(x\right)=\max\left(0,x\right) \tag{13}$$

Let x denote the argument of the Sigmoid function. Additionally, assuming o and x_{in} representing the output of the DNN and the input of the MIMO-NOMA system, respectively, the expression can be formulated as follows:

$$o=f\left(x_{in},w\right)=f^{(n-1)}(f^{(n-2)}(\cdots f^{1}(x_{in}))), \tag{14}$$

The authors propose an effective CNN architecture for the MIMO-NOMA system, illustrated in Fig. 2. The network takes channel vectors and a precoding matrix as input, utilizing a convolutional layer with 64 filters and a Rectified Linear Unit, activation function. Four channels represent real and imaginary parts of channel vectors, precoding matrix, and power allocation factors. A power constraint is integrated into the output layer's activation function. The CNN optimizes precoders, treating power allocation as a nonlinear mapping challenge and enhancing the complex water-filling method. A fully connected layer adapts to diverse environments, reducing noise and distortion. Subsequent layers involve additional convolutional and pooling layers, followed by ten consecutive layers with 64 filters each. A noise layer introduces artificial noise, and the output layer employs a modified Maxout function to enforce power constraints effectively. The expression for the modified Maxout function is as follows:

$$f_{\max}=\min(\max(x_{in}^{T}w\cdots i+b_{i},0),P_{tr}) \quad , (15)$$

The symbol b_i Denotes the bias in the i-th iteration of the optimization process. Employing the MLP-CNN architecture approximates the problem as a continuous function, offering an optimized solution for the MIMO-NOMA system. This approximation allows for efficient handling of the problem that leverages the strengths of both the MLP-CNN.

4.3. Generation of samples and deep learning mechanism

Training the CNN in a deep learning framework requires many transmit data sequences. Channel vector samples are collected through simulations in various channel environments (AWGN, flat fading, and frequency-selective fading). Training is performed individually for each channel, starting with AWGN and extending to other channels like Rayleigh, Rician, and Nakagami-m (m = 3). Initial training in AWGN produces a baseline model $\mathcal{M}_0$, which is further refined in other channels using transfer learning. This approach leverages knowledge from AWGN training to improve the model's performance in different channel conditions [26]. For the MLP-CNN model, assembling a dataset with input samples (CSI matrices) and corresponding target values is crucial. Many CSI scenarios, representing various channel conditions, interference, and noise levels, must be generated or collected. Assessing the similarity between AWGN and new channels, like Rayleigh or Rician, is necessary. The model is benchmarked using the noise of channel after training on other channels to safeguard performance. Each channel sample is linked to target values, such as optimal power allocation coefficients or energy efficiency metrics. Proper division of the dataset into training, validation, and testing sets is vital for the effectiveness of the deep learning-based framework relying on well-defined learning strategies [28].

A unique training process is proposed to enhance the CNN framework for MIMO-NOMA. It utilizes power allocation factors and the precoding matrix as inputs to the MLP-CNN model, allowing it to understand correlations and make predictions for optimized precoders. The CNN is trained offline with channel information and power allocation factors, followed by online learning for adaptation to new scenarios. Online learning involves adjusting model weights and biases using backpropagation and gradient descent. Hyperparameters are iteratively modified, and the model's performance is continuously observed to prevent overfitting [28]. The trained model is evaluated using a testing set and, if needed, fine-tuned based on performance insights. Once the desired criteria are met, the model can be deployed in real MIMO-NOMA systems for power allocation improvements, achieved through a learning mechanism balancing complexity and generalization capability.

5. Deep Learning for Energy Efficiency and Sum Data Rate Optimization

This section introduces an optimization model combining MLP and CNN frameworks, leveraging advanced deep learning techniques to enhance the MIMO-NOMA system. The study focuses on a deep learning-centered strategy, evaluating the robustness of the proposed framework for optimizing sum data rates and energy efficiency. The approach treats the problem as a function effectively processed by a DNN, employing training and testing algorithms (Algorithm 1 and Algorithm 2) for implementation and evaluation.

Algorithm 1 MLP-CNN framework for MIMO-NOMA (Training phase)

Step 1: set the simulation parameters. The input should be the channel vector h_m and precoding matrix P

Step 2: For the deep neural networks (MLP-CNN) framework, generate a wireless channel, then add some noise (AWGN) and other distortion.

Step 3: Generate the training samples' channel vector h_m and precoding matrix P

Step 4: set the framework of the proposed neural network, such as weights, learning rate, solver and batch size

Step 5: Train the MLP-CNN model using the training samples to approximate problem (8) based on the suggested learning mechanism.

Step 6: Update the weights w and the output layers of the CNN model

---

Algorithm 2 MLP-CNN framework for MIMO-NOMA (Testing phase)

Step 1: load the trained MLP-CNN framework.

Step 2: Generate a wireless channel, then add some noise (AWGN) and other distortion for this channel.

Step 3: start processing the proposed model.

Step 4: update the outputs for each layer MLP-CNN.

Step 5: Calculate the power allocation factor, then compute the power allocation coefficient $\beta_{m,k}$

Step 6: Return the precoding matrix P and power allocation coefficient $\beta_{m,k}$

6. Results and Analysis

In this section, we evaluate the performance of the proposed approach designed to optimize the sum data rate and energy efficiency in the MIMO-NOMA system. The study utilizes the 5G Vienna simulator and Python for simulations, employing a dataset containing channel vectors and power factors. A novel strategy is introduced to implement the MLP-CNN framework, considering specific considerations for determining the training sequence length. The simulation focuses on a MIMO-NOMA system with a Base Station located at the center of a circular area with a minimum radius of 500 meters, hosting 512 stationary users randomly distributed within this area.

In the simulation section, the authors consider a propagation channel known as the Nakagami Rice channel. This channel model comprises Line of sight and Rayleigh fading components. The Nakagami-Rice model is a versatile tool for modelling channels with a mix of multipath and line-of-sight features, offering a balance between simplicity and realism. Each user in the system is assumed to have a Rician factor of 10 dB.

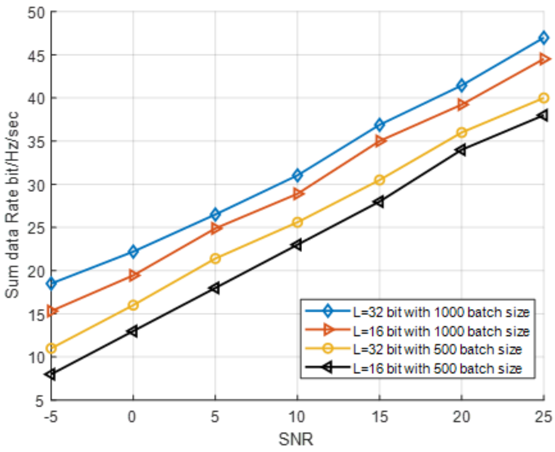

Fig.3. demonstrates the MIMO-NOMA deep learning framework's sum data rate performance for training sequence lengths of 16 and 32 bits.

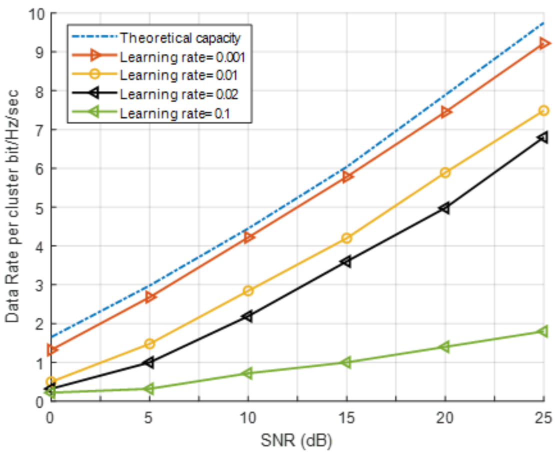

Fig. 4. illustrates the data rate per cluster for various learning rate values (0.1, 0.02, 0.01 and 0.001) and the suggested algorithm (MLP-CNN).

Furthermore, this study incorporates the arrival and departure angles in the analysis, representing crucial spatial information in the MIMO-NOMA system. by establishing the total transmit Power as 18 d.Bm. Additionally, we set the power consumed by each radio frequency P_{RF} = 3.00 mW, Baseband power consumption P_{BB} = 20.0 mW, and power consumption of analog phase shifters P_S = .5 mW as specific power values. It is worth noting that assuming the Signal to noise ratio (SNR) is equal for all users in the system.

6.1. Sum Data Rate Analysis

This section discusses the SNR versus sum data rate analysis in a MIMO-NOMA system optimized using MLP-CNN. Fig. 3 shows performance with different training sequences and batch sizes, considering L=16 bits and 32 bits and batch sizes of 1000 and 500.

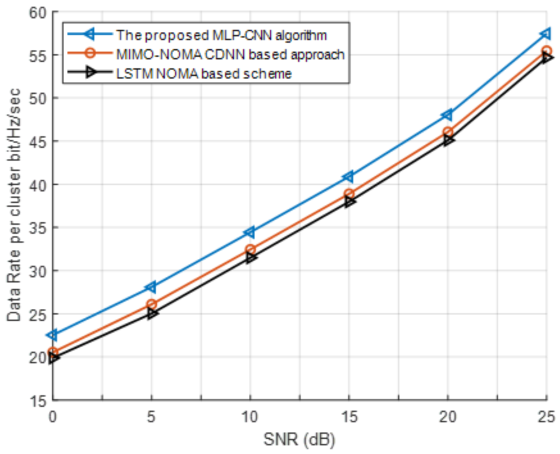

Fig. 5. illustrates the proposed algorithm MLP-CNN framework, the MIMO-NOMA Convolutional Deep Neural Network (CDNN)-based approach [26], and the Long Short-Term Memory (LSTM) NOMA-based scheme [25], compared regarding their sum data rate performances.

Results indicate higher SNR improves the sum data rate, with longer training sequences and larger batch sizes contributing to better performance. Fig. 4 presents the sum data rate across SNR values with varying learning rates, suggesting a lower learning rate achieves data rates closer to theoretical capacity.

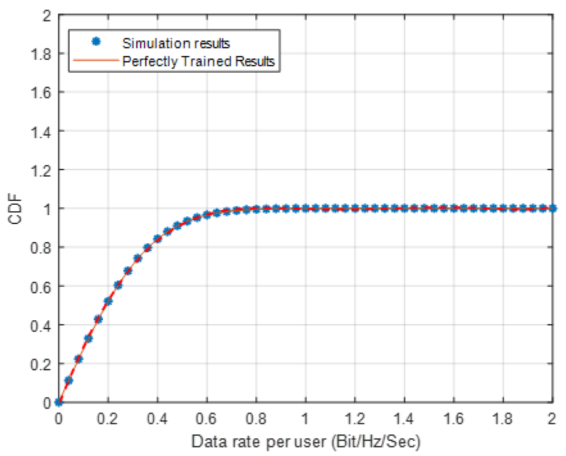

Fig. 6. Illustrates the cumulative distribution function for the data rate per user. For the MLP-CNN algorithm, there are two cases: simulation result and perfectly trained result.

Fig. 5 compares data rates per cluster against SNR for different schemes, showing the proposed MLP-CNN outperforms LSTM-NOMA and CDNN based MIMO-NOMA schemes. The proposed model is effective for systems with mobile users, demonstrating efficiency over systems with stationary users. The analysis focuses on L=32 and a batch size of 1000, assessing the overall system's performance and highlighting the proposed model's effectiveness in time-variant and time-invariant systems. As depicted in fig. 6, the simulation results closely align with the ideally trained outcomes, underscoring the effectiveness of the proposed method.

The proposed MLP-CNN framework exhibits reliability and robustness, performing effectively even in scenarios with severe distortions. Additionally, it is observed that the cumulative distribution function of the data rate curve approaches 1 when the rate of data for the user can reach 0.9 Bit/Hz/Sec. The rapid convergence is achieved by the MLP-CNN scheme, indicating its ability to adapt and optimize system performance quickly.

6.2. Energy Efficiency Analysis

This section assesses the energy efficiency of the proposed system, leveraging results from multiple training rounds. The SNR versus energy efficiency plot in Fig. 7 illustrates that the MIMO-NOMA system surpasses the MIMO-OMA scheme, especially for stationary users. The observed improvement in energy efficiency with rising SNR underscores the advantages of the proposed MIMO-NOMA approach.

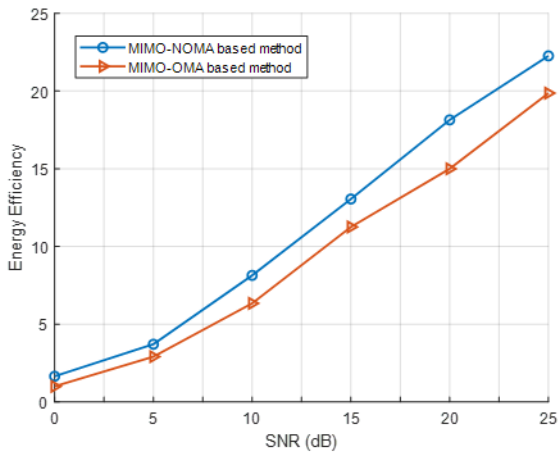

Fig. 7. shows Energy efficiency against SNR comparison between (MIMO-NOMA and MIMO-OMA) methods.

Fig. 8 presents a comparison between the average MIMO-NOMA scheme and the CDNN scheme in terms of energy efficiency. It is evident from the figure that the CDNN-based method achieves higher energy efficiency compared to the typical MIMO-NOMA scheme. This result indicates the superior efficiency of the CDNN algorithm in optimizing energy utilization within the system. Fig. 9 displays the plot of SNR versus energy efficiency for a system that considers mobile users. The analysis reveals that the energy efficiency of the proposed framework-based MIMO-NOMA system improves as the SNR increases.

Insightfully, the proposed framework demonstrates superior power allocation performance, enabling the MIMO-NOMA to transmit Power efficiently. The presented method does not require an online operation because the system is sufficiently prepared through its training stage, excluding the necessity for repeated algorithmic processes. This result reduces energy consumption and computational resources compared to previous approaches requiring repeated algorithm execution.

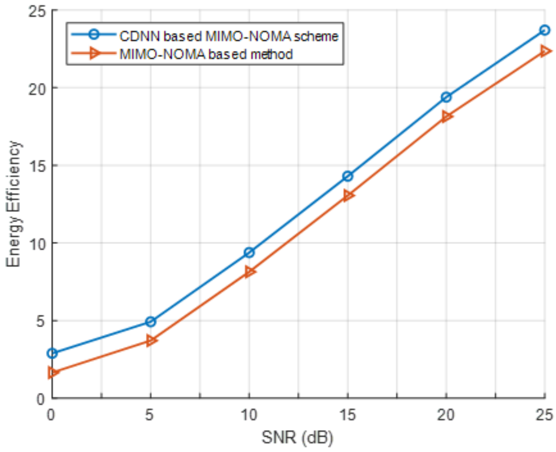

Fig. 8. compares energy efficiency against SNR between the MIMO-NOMA scheme with CDNN and the MIMO-NOMA based approach.

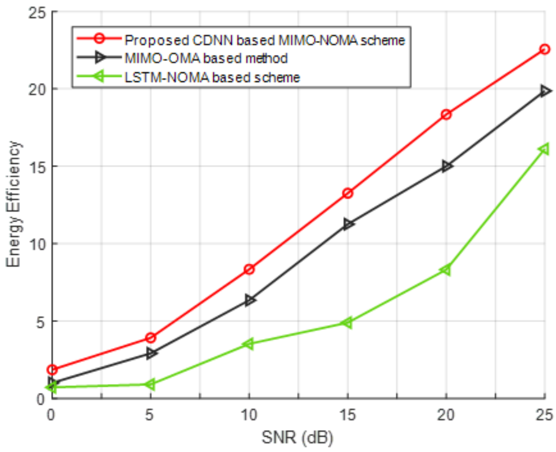

Fig. 9. shows energy efficiency against SNR comparison between CDNN based MIMO-NOMA scheme [26], MIMO-OMA method [27] and LSTM-NOMA scheme.

Furthermore, the proposed technique surpasses the LSTM-NOMA approach, leveraging the capability of MIMO to accommodate multiple users with a more significant number of antennas at the base station. Despite the LSTM-NOMA scheme benefiting from deep learning methods, the proposed approach demonstrates superior performance.

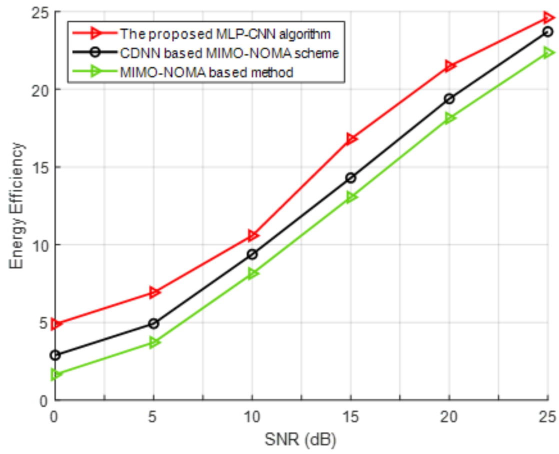

Fig. 10. compares energy efficiency against SNR among the proposed MLP-CNN algorithm, CDNN-based MIMO-NOMA, and MIMO-NOMA methods.

6.3. Deep Learning and Training Progress Analysis

This section investigates the training and testing of the proposed MLP-CNN model, which incorporates deep learning algorithms into the MIMO-NOMA system. The learning mechanism involves training the model using the provided dataset, optimizing its weights and biases through backpropagation, and improving its performance. The objective is to strike a balance between the complexity of the model and its generalization capability, ensuring it avoids overfitting and achieves the desired enhancements in energy efficiency. During the initial stage of training, the study observed that the minimum mean square error graph for both the validation loss and training loss ranges between 0.40 and 0.35, as depicted in Fig. 10.

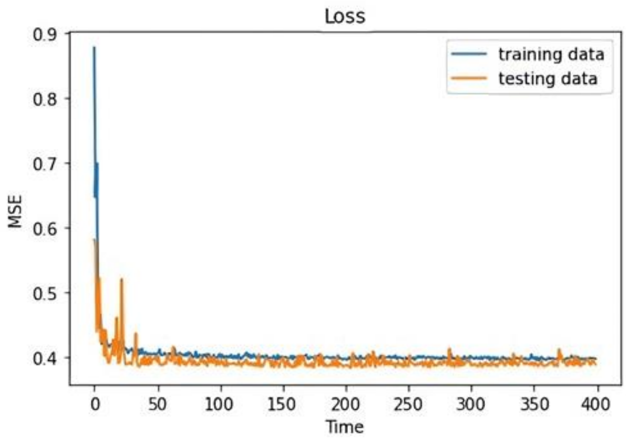

Fig. 11. Shows the first phase of training Mean square error (MSE) for training and validation data of the proposed MLP-CNN framework.

In the second training phase, as shown in Fig. 11, the authors analyse the MSE against time, with the number of epochs reaching approximately 400 for both the training and testing datasets. These training and testing progressions demonstrate the iterative improvement and convergence of the model, as evidenced by the decrease in MSE and the satisfactory performance achieved by the MLP-CNN model.

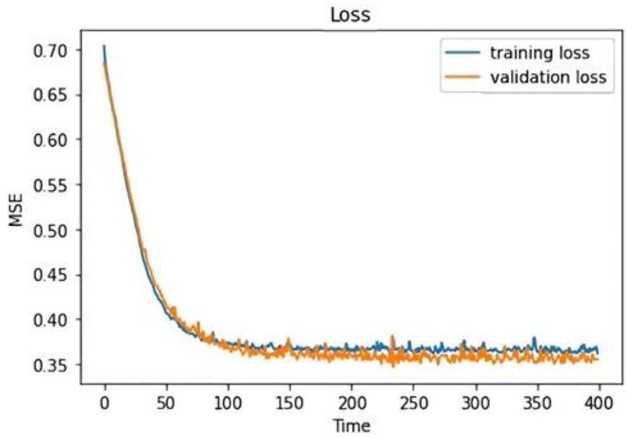

Fig. 12. Shows the second phase of training MSE for training and testing data of the proposed MLP-CNN framework.

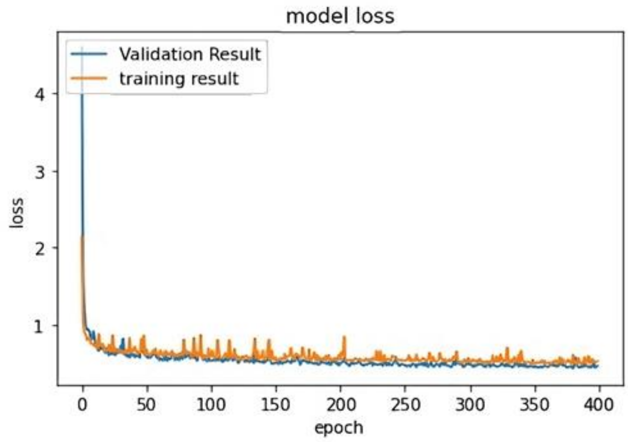

Fig. 13. Illustrates the loss of validation and training results over time for the proposed MLP-CNN framework model.

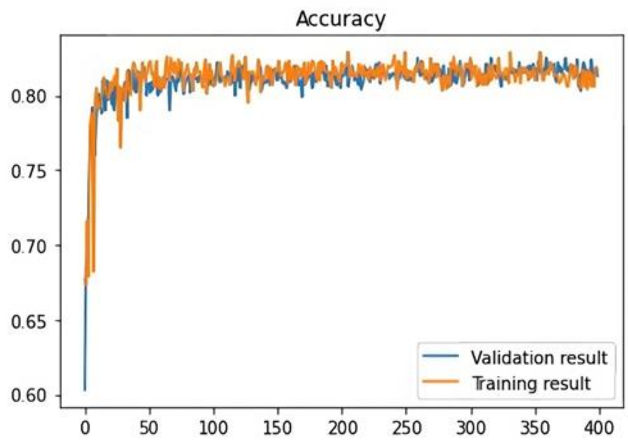

Fig. 14. shows the accuracy of the first step of the training phase for the proposed MLP-CNN framework for both the validation and training results.

Fig. 12 illustrates the MSE curve for the proposed MLP-CNN model consistently stays below one, indicating excellent performance after only a few training steps. This figure demonstrates the comprehensive training and the reliability of MIMO-NOMA scheme. The substantial difference between validation and training errors exceeds expectations, highlighting the exceptional generalization ability of the proposed framework showcasing high accuracy in learning network inputs.

The graph shows the validation and training results loss over time for the proposed framework. It provides insights into how the loss changes throughout the operation time of the model in Fig. 13. In the initial stage of learning, the accuracy curve shows a steady increase over time, as depicted in Fig. 14. Both the validation and training results exhibit improvement, rising from 60% to 80%. This progress is observed during the first stage of training. In the second stage, the accuracy further increases to 88% for both the validation and training results, as illustrated in Fig. 15. These findings highlight the effectiveness of the proposed framework in achieving higher accuracy and improved performance.

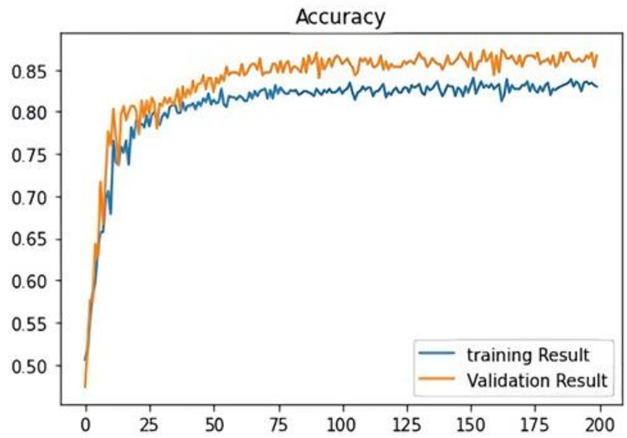

Fig. 15. shows the accuracy of the second step of the training phase for the proposed MLP-CNN framework for both the validation and training results.

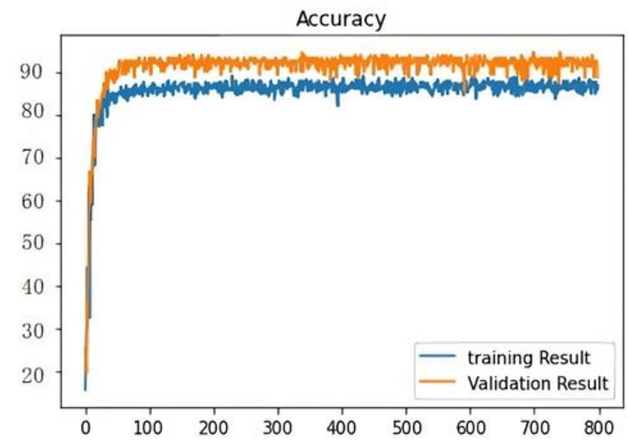

Fig. 16. Shows the Accuracy of the training phase progression for the proposed MLP-CNN framework for both the Validation and Training results.

Fig. 16. reveals that in the final stages of training, both the

validation and training datasets achieve maximum accuracy, surpassing 93%. This result indicates that the accuracy curve has reached its peak performance. Additionally, Fig. 17 demonstrates that the training dataset's loss decreases to less than 0.001 in the final stages of training, indicating an improvement compared to the earlier training phases. These results provide strong evidence that the proposed framework can achieve very high accuracy and superior performance when deep learning methods are integrated with both MIMO and NOMA techniques.

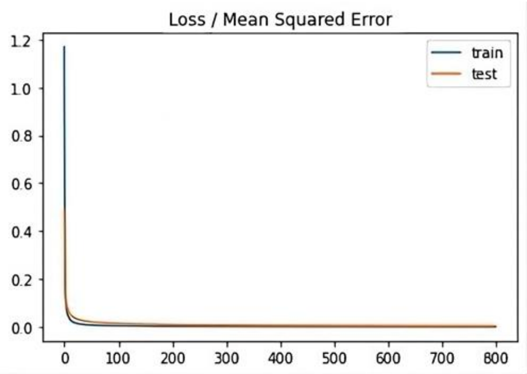

Fig. 17. Shows the training loss and testing loss for the last step of the proposed MLP-CNN framework.

7. Conclusion

This research presents an effective strategy for optimizing power allocation that integrates deoptimizing learning with the MIMO-NOMA system. The proposed approach employs the MLP-CNN framework with tailored activation functions in each layer. The framework undergoes offline and online learning stages to capture crucial spatial features of the MIMO-NOMA system and ensure efficient model training. By using deep learning descriptive and mapping capabilities, the presented method facilitates precise estimation of channel state information, enhancing user performance. The power allocation optimization challenge is effectively tackled through the approximation prowess of the MLP-CNN model. Thorough simulations have substantiated the superior performance and resilience of the CNN-based MIMO-NOMA framework. Future work will focus on extending the research to time-varying fading scenarios and Intelligent Reflected Surfaces, incorporating cognitive radio networks, and addressing security and system capacity concerns.

Acknowledgements

The authors are grateful to The University Putra Malaysia Faculty of Computer and Communication Engineering and to the Wireless and Photonic Networks Research Centre of Excellence (WiPNET), Faculty of Engineering and Technology.

Author contributions

Kamil Audah: Conceptualization, Methodology, Software, Field study **Kamil Audah:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Walaa Hussein:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] S. P. Kumaresan, C. K. Tan and Y. H. Ng, "Efficient User Clustering Using a Low-Complexity Artificial Neural Network (ANN) for 5G NOMA Systems," IEEE Access, vol. 8, pp. 179307-179316, September 2020.

[2] M. K. Hasan, M. Shahjalal, M. M. Islam, M. M. Alam, M. F. Ahmed, and Y. M. Jang, “The Role of Deep Learning in NOMA for 5G and Beyond Communications,” International Conference on Artificial Intelligence in Information and Communication (ICAIIC), pp. 303-307, February 2020.

[3] M. Katwe, K. Singh, P. K. Sharma, C.-P. Li, and Z. Ding, “Dynamic User Clustering and Optimal Power Allocation in UAV-Assisted Full-Duplex Hybrid NOMA System,” IEEE Transactions on Wireless Communications, vol. 21, no. 4, pp. 2573-2590, September 2021. https://doi.org/10.1109/twc.2021.3113640

[4] H. Zhang, H. Zhang, W. Liu, K. Long, J. Dong, and V. C. Leung, “Energy Efficient User Clustering, Hybrid Precoding and Power Optimization in Terahertz MIMO-NOMA Systems,” IEEE Journal on selected areas in communications, vol. 38, no. 9, pp. 2074-2085, June 2020. https://doi.org/10.1109/jsac.2020.3000888.

[5] G. Li, M. Zeng, D. Mishra, L. Hao, Z. Ma, and O. A. Dobre, “Energy-Efficient Design for IRS-Empowered Uplink MIMO-NOMA Systems,” IEEE Transactions on Vehicular Technology, vol. 71, no. 9, pp. 9490-9500, May 2022.

[6] Y. Song, J. Tang, C. Lin, W. Feng, Z. Chen, D. K. C. So, and K.-K. Wong, “Energy Efficiency Optimization for PSOAM Mode-Groups Based MIMO-NOMA Systems,” IEEE Transactions on Communications, vol. 70, no. 8, pp. 5679-5692, June 2022.

[7] N. Prabakaran and R. P. Devi, “An Improved Deep Learning Framework for Enhancing MIMO-NOMA System Performance,” Multimedia Tools and Applications, vol. 82, pp. 1-28, August 2023.

[8] Sk, Khaleelahmed, and VenkateswaraRao N., “An Approach for Energy-Efficient Power Allocation in MIMO-NOMA System,” International Journal of

Electronics, vol. 109, no. 6, pp. 953-970, June 2022.

[9] A. Bhardwaj, R. Raman, J. Singh, K. Pant, N. Yamsani, and R. Yadav, "Deep Learning-Based MIMO and NOMA Energy Conservation and Sum Data Rate Management System," 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), pp. 866-871, May 2023.

[10] M. Ravi, T. A. Sheikh, and Y. Bulo, "Improve Energy Efficiency and Minimise BER in MIMO-NOMA System With Max-Min Power Control Algorithm," International Journal of Systems, Control and Communications, vol. 14, no. 3, pp. 254-273, November 2023.

[11] S. Rajak, P. Selvaprabhu, S. Chinnadurai, A. S. Hosen, A. Saad, and A. Tolba, "Energy Efficient MIMO-NOMA Aided IoT Network in B5G Communications," Computer Networks, vol. 216, p. 109250, October 2022.

[12] A. Jawarneh, M. Kadoch, and Z. Albataineh, "Decoupling Energy Efficient Approach for Hybrid Precoding-Based mmWave Massive MIMO-NOMA With SWIPT," IEEE Access, vol. 10, pp. 28868-28884, February 2022.

[13] V. Andiappan and V. Ponnusamy, "Deep Learning Enhanced NOMA System: A Survey on Future Scope and Challenges," Wireless Personal Communications, vol. 123, no. 1, pp. 1-39, March 2022.

[14] R. Zhang, K. Xiong, Y. Lu, D. W. K. Ng, P. Fan, and K. B. Letaief, "SWIPT-Enabled Cell-Free Massive MIMO-NOMA Networks: A Machine Learning-Based Approach," IEEE Transactions on Wireless Communications, vol. 18, pp. 1 – 1, November 2023.

[15] S. Mirbolouk, M. Valizadeh, M. C. Amirani, and S. Ali, "Relay Selection and Power Allocation for Energy Efficiency Maximization in Hybrid Satellite-UAV Networks With CoMP-NOMA Transmission," IEEE Transactions on Vehicular Technology, vol. 71, no. 5, pp. 5087-5100, February 2022.

[16] A. B. Adam, Z. Wang, X. Wan, Y. Xu, and B. Duo, "Energy-Efficient Power Allocation in Downlink Multi-Cell Multi-Carrier NOMA: Special Deep Neural Network Framework," IEEE Transactions on Cognitive Communications and Networking, vol. 8, no. 4, pp. 1770-1783, August 2022.

[17] S. Sabapathy, A. Krishnan, N. Nedoumarane, S. Maruthu, and D. N. K. Jayakody, "Deep Learning Based Simultaneous Wireless Information and Power Transfer Enabled Massive MIMO-NOMA for Beyond 5G," International Conference on Signal Processing, Computation, Electronics, Power and Telecommunication (IConSCEPT), pp. 1-6, May 2023.

[18] M. K. Beuria and S. S. Singh, "Performance Analysis of Cooperative NOMA With Optimized Power Allocation Using Deep Learning Approach," Wireless Networks, vol. 29, pp. 1-16, October 2023.

[19] R. Aldebes, K. Dimyati, and E. Hanafi, "Genetic Algorithm for Optimizing Energy Efficiency in Downlink mmWave NOMA System With Imperfect CSI," Symmetry, vol. 14, no. 11, p. 2345, November 2022.

[20] K. R. Chandra and S. Borugadda, "Multi Agent Deep Reinforcement Learning With Deep Q-Network Based Energy Efficiency and Resource Allocation in NOMA Wireless Systems," 2nd International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), pp. 1-8, April 2023.

[21] A. Kumar and K. Kumar, "Deep Learning-Based Joint NOMA Signal Detection and Power Allocation in Cognitive Radio Networks," IEEE Transactions on Cognitive Communications and Networking, vol. 8, no. 4, pp. 1743-1752, July 2022.

[22] S. Norouzi, B. Champagne, and Y. Cai, "Joint Optimization Framework for User Clustering, Downlink Beamforming, and Power Allocation in MIMO-NOMA Systems," IEEE Transactions on Communications, vol. 71, no. 1, pp. 214-228, November 2022. https://doi.org/10.1109/tcomm.2022.3222374.

[23] Z. Zhang, M. Hua, C. Li, Y. Huang, and L. Yang, "Beyond Supervised Power Control in Massive MIMO Network: Simple Deep Neural Network Solutions," IEEE Transactions on Vehicular Technology, vol. 71, no. 4, pp. 3964-3979, January 2022.

[24] H. Huang, Y. Yang, Z. Ding, H. Wang, H. Sari, and F. Adachi, "Deep Learning-Based Sum Data Rate and Energy Efficiency Optimization for MIMO-NOMA Systems," IEEE Transactions on Wireless Communications, vol. 19, no. 8, pp. 5373-5388, May 2020.

[25] X. Wei, H. Al-Obiedollah, K. Cumanan, Z. Ding and O. A. Dobre, "Energy Efficiency Maximization for Hybrid TDMA-NOMA System With Opportunistic Time Assignment," IEEE Transactions on Vehicular Technology, vol. 71, no. 8, pp. 8561-8573, August 2022.

[26] H. Han, X. Jiang, W. Lu, W. Zhai, Y. Li, N. Kumar, and M. Guizani, "A Multi-Agent Reinforcement Learning Approach for Massive Access in NOMA-URLLC Networks," IEEE Transactions on Vehicular

Technology, vol. 10, pp. 1-7, July 2023.doi: https://doi.org/10.1109/tvt.2023.3292423.

[27] W. Lee, H. Lee, and H.-H. Choi, "Deep Learning-Based Network-Wide Energy Efficiency Optimization in Ultra-Dense Small Cell Networks," IEEE Transactions on Vehicular Technology, vol. 72, pp. 8244 - 8249, January 2023.

[28] A. J. Muhammed, H. Chen, A. M. Seid, Z. Han, and Q. Yu, "Energy-Efficient Resource Allocation for NOMA HetNets in Millimeter Wave Communications," IEEE Transactions on Wireless Communications, vol. 22, pp. 3790 - 3804, November 2022.