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Enhancing detection performance in massive MIMO O-NOMA systems using deep learning

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Abstract
There are problems in O-NOMA systems, which can be addressed using the method of deep learning called DLM, that result from overlapping and entangling of the system signals. The NOMA method increases the efficiency of the optical frame spectrum, allowing multiple people to use the same moment and frequency resources. However, the interference patterns Complex and non-stationary channel conditions in NOMA-DLM systems pose challenges to traditional detection methods, and by taking advantage of deep neural networks, these methods can surpass these challenges and as such improve their performance in detection. This article gives us a brief insight into the primary aspects and benefits of DLM detection methods when integrated with M-MIMO O-NOMA systems with underlying features like training procedures in addition to network design. DLM networks are designed to work with received codes or decoded data streams from the input signal, power allocation coefficients, additional information, and regression enhancement are also considered when updating the network parameters in the course of training this study also aims at examining the challenges faced by deep learning when applied in O-NOMA systems.

Keywords: DLM, NOMA, MIMO, regression optimization

1. Introduction

The introductory section describes the development and implementation of advanced wireless communication technologies, namely M-MIMO and optical non-orthogonal multiple access (O-NOMA) systems. The main aspects of channel state information (CSI) calculation and data discovery are mentioned to facilitate signal extraction.

It is worth noting that extending NOMA principles from wireless to optical domains enhances spectral efficiency and concurrent user support, which confirms its ability to improve network capacity, spectrum efficiency, and reduce latency. CSI identification and data discovery are indicated as critical precursors for correct recovery of broadcast signals, and O -NOMA refers to an increase in the use of NOMA to double the user load capacity in optical networks [1].

The concepts of M-MIMO and O-NOMA are introduced in relation to advanced radio system design and next generation optical communications networks. Both technologies aim to maximize bandwidth utilization by multiplexing at different power levels. The necessity of signal detection to separate transmissions and decode the Encryption of individual user data streams with an emphasis on their ability to increase network load capacity and spectrum efficiency through spatial multiplexing and non-orthogonal signal coding techniques [2]. CSI feedback requirements and signal identification are specified prior to data decoding O-NOMA is a modification of NOMA that provides complementary improvements in Performance of optical systems. For signal detection in M-MIMO systems: Estimate channel state information and decode data.

Scanning channels through orthogonal trial sequences sent from users to the base station allows individual channel responses to be identified and the base station then detects to distinguish transmitted symbols from received mixtures. Linear techniques such as zero effect and MMSE detection are commonly used although iterative methods also see use through serial interference cancellation schemes, channel estimation and data recovery are identified as the fundamental processes that enable signal identification in M-MIMO architectures [3].

Code-based heuristic feedback from user devices to the base station facilitates the creation of channel profiles for each user. A variety of detection models are implemented at the base station with the goal of distinguishing codes from noisy scrambled transmissions including direct array methods in conjunction with More complex redundancy strategies repeatedly eliminate interference While the main dual operations of channel estimation and centralized data detection clarify the M. MIMO signal, temporary pilot signals sent from users to the base station allow individual propagation paths to be derived [2].

Linear and redundant detection logic is applied at the base station seeking to extract transmitted data packets from combined transmissions encountering noise and interference. Learning-based detection is also referred to and the channel is scanned by exchanging orthogonal pilot codes and subsequent differentiation of the signal at the base station through decoding schemes. Linear or redundant encoders as the basic elements of M-MIMO function [3, 4].

Zero forcing, MMSE and serial interference cancellation serve as representative solution strategies although experimental contamination and non-linear channel variations pose persistent challenges that require further mitigation approaches and we find priority of channel estimation over user-generated experimental codes and subsequent data decoding operations performed at the base station to enable Signal identification within M-MIMO frames, both simple matrix processing and elimination of extensive iterative interference are used in the computation. Experimental contamination mitigation and machine learning integration represent active areas of subsequent research interest for enhancing discrimination under adverse conditions.

2. Literature review

The section reviews previous scholarship that addresses signal detection bottlenecks within wideband MIMO resulting from diverse interference sources, Early DL-based solutions and model-based models incorporating deep learning are evaluated with noting achievements but weak demands for improved computational efficiency and scalability for Dynamic Channel, Promising ways to reduce complexity while maintaining performance through accelerator schemes and matrix partitioning are also pointed out.

A variety of previous efforts applying deep learning and iterative optimization techniques aiming to enhance signal identification under interference are summarized. Achievements in reducing error rates using DL frameworks are balanced with the need for extensive training data. Reducing the computational burden without sacrificing detection quality emerges as a recurring theme although the challenges of non-ideal settings and lack of full channel information are also cited [5].

A literature evaluation indicates preliminary work to innovate DL-based receivers and model-based integration of deep network architectures that seek to improve interference effects. Successes in going beyond traditional solutions are determined by open questions about appropriate scaling and accommodation of nonlinear channels. Complexity reduction is demonstrated in Prominent in subsequent studies through strategies such as matrix partitioning and iterative acceleration, the AA sample is identified from previous contributions that seek to explicitly address the barriers to signal recovery within MIMO architectures and benchmark early applications of deep learning and iterative optimization [6]. With lowering error metrics, questions remain. Around data-intensive needs and dealing with diverse conditions, simplifying the computation burden emerges as a focal point for developing methods to support performance under complexity constraints [7].

The section reviews previous scholarship exploring DL and model-guided models aimed at solving interference-imposed MIMO signal detection problems, the achievements and limitations related to complexity, generalizability and ability to flexibly respond to channel dynamics are drawn and thus reducing complexity and maintaining detection quality come to the surface with focus on the distinctive design of the successful work discussed [8].

Recently a lot of attention has been paid to O-NOMA because of its aptitude for enhancing the capacity and efficiency of optical networks hence making it possible to tap the valuable optical spectrum in radio networks [9]. "In M MIMO-NOMA architectures, application of a proposed signal detection algorithm find many benefits, significantly drops calculation complexity, allows a big MIMO environment even in real time and Deep learning algorithms are capable of adjusting to challenging and constantly evolving channel conditions, which increases their capabilities and efficiency [10]. In addition, it manages nonlinearity and interference present in M-MIMO-NOMA scenarios with high interference, thus improving spectrum performance, experience of users and overall communication system performance.

3. Proposed system model

This system has many parts which cooperate so that information can be sent and received efficiently including the transmitter, the optical medium, and the receiver; on the sender's side, the information which is meant to be sent goes through various controlling mechanisms after which it gets encrypted for transmission. Fig 1 shows the O-NOMA system block in detail.

The encrypted data is divided into several streams where it is assigning a specific power level to each stream. Power allocation, a key component of NOMA technology, makes it possible to transmit multiple signals in the same spectrum resources using different power levels [8, 10].

Segmentation is usually performed based on channel conditions and users expected QoS levels. The data streams are combined using an overlay approach. Once produced and powered up, A device such as a direct intensity modulation/detection (IM/DD) converter transforms the integrated signal from electrical to optical form, facilitating its transmission through the optical medium.

The optical channel is how a sender sends a message to a receiver. These components that make up the message are such as optical fibers, amplifiers, and others.

During the process of traveling through the channel, an optical signal may be affected by modulation and noise, lowering the signal quality. For the consideration of these effects, one should look at the properties of the channel as well as adopt specific signal processing methods like equalization and dispersion [6].

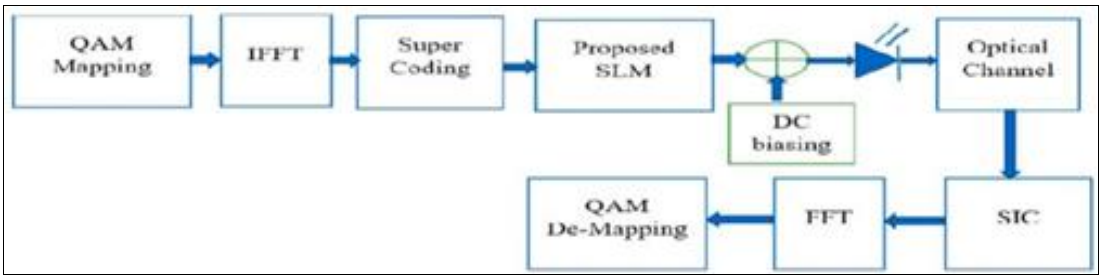


Fig 1: O-NOMA structure

A light detector at the receiver side turns the digital optical signal back to an electric signal. After that, the separate data streams that have been provided by different users removed from the electric signal through processing. In NOMA, because many signals are transmitted at the same time, the receiver needs to have sophisticated mechanisms that enable it separate signal, thus using signal-separation technology to decipher individual streams.

The received signal will be processed through, incoming stronger signals can be filtered out for decoding by the recipient before getting rid of them. For regaining the smaller signals, this should be redone until total streams contain actual values and not noise or anything else descriptive. The sender must then decrypt data streams before restoring the initial information using more advanced signal processing and decoding methods [11].

These techniques might range from editing to decoding, correction of errors. Data that has been accurately collected will be further processed and transmitted to relevant consumers or programs. A schematic of an O-NOMA system demonstrates how multiple data streams with different power levels are combined and transmitted concurrently through a single optical channel, with the signal processing unit at the receiving end conducting precise extraction as well as decoding of multiple types of information.

4. Mathematical representation of an M-MIMO system

M-MIMO (Massive Input Multiple Output) is a technology used in wireless communications systems to improve spectral efficiency and increase system capacity. It takes into account different parameters such as channel situation, noise and interference [12].

There are parties or users K in the M-MIMO system and every user i (i.e. i = 1::K) sends a data s(i) from a constellation set S(i) whose transmitted signal origin is mi with respect to Eq (1) which represents user i:

$$x(i) = \sqrt{P(i)s(i)} \tag{1}$$

At this point, consider P(i)x(i)= √(P(i)s(i)) as the user i's transmission power allocation and, to reach the aimed transmission power level, the signal's s(i) symbol is registered using √P(i).Therefore, the equation for the entire vector of signals released by all users can be given as follow:

$$x = [x(1),x(2),\ldots,x(K)]^T \tag{2}$$

A matrix H that depicts the transmission from each user antenna to the base station antennas is utilized for simulating a channel in a large M-MIMO system. H is the M x N channel matrix, where M denotes the total number of user antennas and N signifies the number of base station antennas. The signal received by the base station is represented by Equation (3):

$$y=hx+2 \tag{3}$$

In the following equation, y will represent the signal recognized basically while n symbolizes the noise vector having a covariance matrix σ^2I where I is an identity matrix. The objective when it comes to data detection within Massive Multi-Input Multi-Output systems is to find out or estimate broadcasting codes s(i) on per user bases; in other words, this is done with an aim of optimizing for conditional probability P(y|s(i, H) of likeness between received signal y and transmitted code word s(i) given the channel matrix H represented by a mathematical model defined in equation 4:

$$\hat{s} = \operatorname{argmax} \Pi(i)P(y|s(i), H) \tag{4}$$

Here, ŝ is the estimated symbol vector

M-MIMO systems for accurate recognition requires proper channel state information (CSI). The base station sends known probing codes to subscribers as part of the channel estimation protocol [13]. Subscribers return the probed signals in parallel with a pilot matrix C of dimensions L x N (L represents the total number of pilot symbols, while N denotes the number of employing antennas). Least squares can be one approach to calculate the estimated channel matrix Ĥ. as shown in equation (5):

$$\hat{H} = H\hat{C}^T(\hat{C}\hat{C}^T + \sigma\text{^}2I)\text{^}(-1) \tag{5}$$

Where received experimental matrix is Ĉ. Next, the estimated channel matrix Ĥ is employed to detect the data. This mathematical system model serves as a foundation for the analysis and optimization of M-MIMO performance.

The model takes into account the relationships between transmitted and received signals, encompassing channel characteristics, and emphasizes the processes of data detection and channel estimation. The specifics of the channel model, along with various detection and estimation algorithms, may vary based on system design and underlying assumptions.

The proposed DL detection model for O-NOMA uses deep neural networks to improve detection efficiency in NOMA systems. NOMA is a technology that allows many users to use the same resources and thus increase spectral efficiency in optical communication systems [14]. However, detection in NOMA may be difficult due to interference caused by overlapping signals.

5. Mathematical model of DL algorithm

An artificial neural network was used to train the network directly from data for a detection model based on DL. It considers various noise scenarios such as power assignment, interference, and channel state in a variety of settings with labeled examples drawn from a big dataset.

An AI like text can be rephrased into a human form. Also ensure a text rewrite with less perplexity and increased burstiness yet maintaining the word count and HTML elements as in "The input to the network usually comprises the received signal, represented as a vector with complex values, along with supplementary information such as power allocation parameters and channel conditions. The network processes this input to generate an estimate of the transmitted codes or the decoded data stream [15].

The training process involves two main stages: data generation and network training. The data generation phase involves producing a dataset comprised of labeled training samples through simulating O-NOMA system transmission and reception processes while integrating various channel models as well as interference scenarios.

The network is trained using training examples from repeatedly feeding it inputs and adjusting its weights through back propagation and gradient descent optimization. The aim is to reduce the discrepancy between the anticipated and actual outputs through a loss function.

As soon as the training is done, the DL detection model can be put into operation in real-world settings, where it will detect transmitted codes or decode data streams in an O-NOMA system hence deliver consistent and effective performance in terms of detection. Handling complex interference patterns, adaptability in diverse channel settings, make the DL approach preferable over other methods when used in actual NOMA systems that operate under various conditions [16]. Fig 2 shows a schematic of DLM procedures.

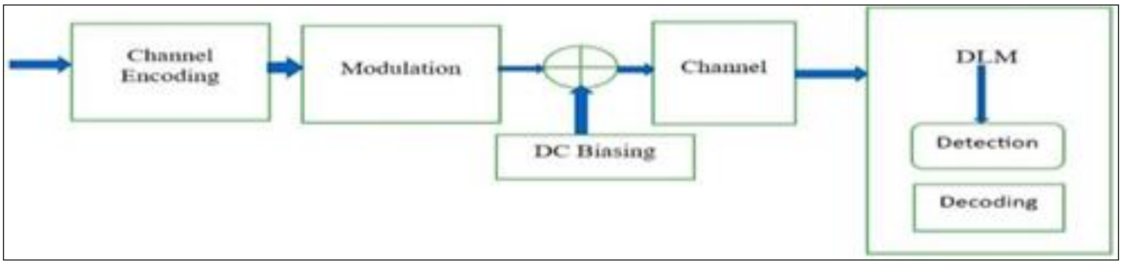


Fig 2: Schematic of DLM procedures

The math model of DL procedure shows the network structure and training procedures. Both types of layers: convolutional and full connection ones have been included into this study. L denotes the input. Each layer performs its transformation on the input, resulting in an output. Finally, the network's output represents expected codes or decoded data streams.

Different network architectural specifications, such as system design and requirement factors may determine the number of layers, convolutions size and leak rate. Mathematical model is a framework that enables better understanding of structure and functions the DL-based O-NOMA detection system.

In the training procedure, the optimal network parameters defined as θ are derived from N labeled training example data from D in such a manner as to minimize the mean loss that occurs at each training example. This implies that every X(i) of the N labeled data points in D represents an instance where x is the input while y denotes ground truth label (Y(i)) [13].

The aim is to seek those network parameters, θ, that reduce the error between the expected output, Y, and the actual truth output, Y(GT). This is done by creating a loss function, L(Y, Y(GT)), that quantifies how much Y differs from Y(GT). Obtain the mean loss over the training examples using the equation:

$$J(\theta) = (1/N) * \sum L(Y,Y(GT)) \quad (6)$$

The adjustment of the network parameters (represented as θ) is carried out using gradient descent optimization, where the update is performed as follows: θ <- (θ − α * ∇J(θ)). In this equation, α denotes the learning rate, and ∇J(θ) represents the gradient of the loss function with respect to θ.

During inference given a new input as H(i)= f(i)(H(i-1)) where f(i) is the transformation applied by the ith layer, the final predicted output is given by Y(prediction) = H(L) where L is the layer index Last.

The mathematical model captures the essence of O-NOMA, Nevertheless, because of the diversity of the problems characteristics and performance goals, the activation functions and the loss function formulations might differ. In addition, it is essential to select the proper mathematical models for every part by considering the specific demands of the problem [14].

The topology of a deep neural network is shown in Fig 3. Deep neural networks have higher number of hidden layers than which are then artificial neural networks and this allows them to apprehend complex patterns more accurately. These layers are attached in series in such a way that the input of a given layer is the same as the output gotten from it.

Fully connected neural networks, often referred to as network topology, feature a structure where each neuron in one layer is linked to every neuron in the subsequent layer.

Convolutional Neural Networks are commonly used in computer vision Convolutional layers for feature extraction

Convolution decreases the output size and the number of parameters, enhancing the efficiency of the training process. Dropout layers can be added to prevent overfitting by randomly removing neurons during training [17].

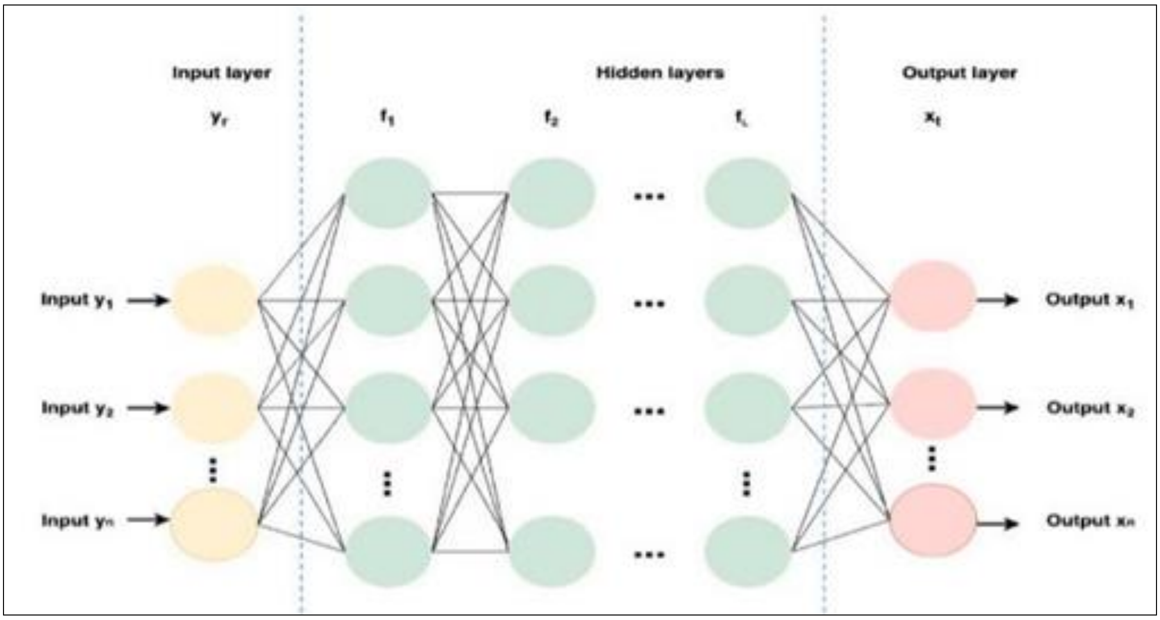


Fig 3: Structure of Neural network.

Deep learning (DL) is being applied to optimise the name of the node method (O-NOMA) in terms of performance, processing speed and memory. But it has its own drawbacks; these include complex nature which can be broken down among the following complexities [18]:

One of the complexities of training is based on the requirement by deep learning models for so much data that has been tagged which may end up taking too long and being complex to come up with. It is important that the dataset has various scenarios to guarantee its durability as well as ability to cover all possibilities. Training deep neural networks also demands sufficient resources.

6. Model complexity: DNN consist of numerous layers and parameters, this makes it hard to design the perfect network architecture. Henceforth, a close and experimental study needs to choose the correct activation functions, optimization algorithms as well as regularization techniques. Computational requirements and times get more enhanced when the model becomes more complicated with larger or deeper networks.

Computational complexity refers to the arduousness of DL models mostly when training. The training stage particularly while implementing backward and forward propagations on big data sets needs a lot of processing capacity.

The hardware may be modular. Specialized graphics processing such as GPUs or accelerators is necessary to handle the computational demands.

Generalization complexity can only be achieved for deep learning (DL) models which manage to regularize properly while at the same time hyperparameter tuning correctly. Selecting the right network architecture, choosing among variety of regularizations techniques as well as determining correct set up for hyperparameters is challenging with possible and practically often one would apply optimization techniques trial and error or advanced ones. An issue that can't be ignored is that although it's okay with training set performance indicators yet novel points aren't captured well always_utilsized datasets.

The interpretability of deep learning models is complex. They are often viewed as black boxes because they are so complicated. Understanding how the model makes its predictions or decisions can be hard. Research is still being done to explain the patterns and steps deep neural networks use to make decisions. Unlike detection techniques, classical approaches offer more reasonable explanations and permit one grasp what really lies beneath algorithms' surface.

Even though these complexities exist, DL-based detection methods have certain benefits in managing complex interference patterns as well as adjusting to new channel states. Thorough network design, effective training procedures and use of advances in resources are some ways of reducing these complexities. There is ongoing work to account for these complexities.

Make DL more intuitive and efficient for a wide application range, including O-NOMA detection. A user clustering strategy can be used in 5G networks to manage effectively a complex and dynamically changing wireless communication environment. User grouping is determined by factors such as modulation techniques, S/N ratios, mobility patterns, and traffic requirements [12, 19]. Applying DL methods, such as networking, we use neural on such user groups to better signal identification and resource distribution. The DL model is capable of recognizing patterns and features of all user groups, which helps make more accurate and faster detection within these groups. In view of learning this information from multiple users it can improve network performance, resource utilization as well as taking into account various requirements or behaviors characteristic for each individual user '_group.

Result: Time Independent (TD-MIMO) is used to describe a communications system that includes multiple transmitters and receivers taking time into account. The transmission and reception signals are expressed by a matrix of wireless channels and we have a MIMO TD system consisting of M transmitters and N receivers. The transmission signal from device i at time t can be expressed using the vector s_i(t) such that i ranges from 1 to M. Similarly, the reception signal at device j at time t can be expressed using the vector r_j(t) such that j ranges from 1 to N When a signal is transmitted from the transmitting devices to the receiving devices, the signal is affected by the wireless channels H between the devices. The communication channel between device i and device j can be expressed using the matrix H_ij. Therefore, the general equation for MIMO TD system can be written as follows:

$$r_{j(t)} = \Sigma \left[H_{ij} * s_{i(t)}\right] + n_{j(t)} \quad (7)$$

Where;

- r_j(t) is the receiving signal in device j at time t.
- H_ij is an element in matrix H that represents the communication channel between device i and device j.
- s_i(t) is the transmission signal of device i at time t.
- n_j(t) is the random input into machine j at time t.

The primary goal of the MIMO TD system is to estimate the H-matrix to achieve recovery of the original signal at receiving devices. Advanced techniques such as linear stochastic modeling (LMMSE) or low bound estimation (LLS) are used to achieve this goal. All data related to the system (m) is calculated and stored in an Excel file for the training and testing process

The model testing process takes place after it is trained on training data and verified on validation data. The process includes:

Test data is formed the input data for the form (X_test) is converted into a cell array (X_test_cell) using the mat2cell function. Each element in X_test is transformed into a separate cell in X_test_cell and then the model is applied to the test data where the classify function is used to classify the test data (X_test_cell) using the trained model (net). Model predictions (Y_pred) are generated based on test data and accuracy is calculated by comparing model predictions (Y_pred) with actual targets (Y_test). The number of correctly predicted cases is summed and divided by the total number of cases in the test data to get the final accuracy. Fig 4 presents evaluation of the model on test data in Massive MIMO O-NOMA

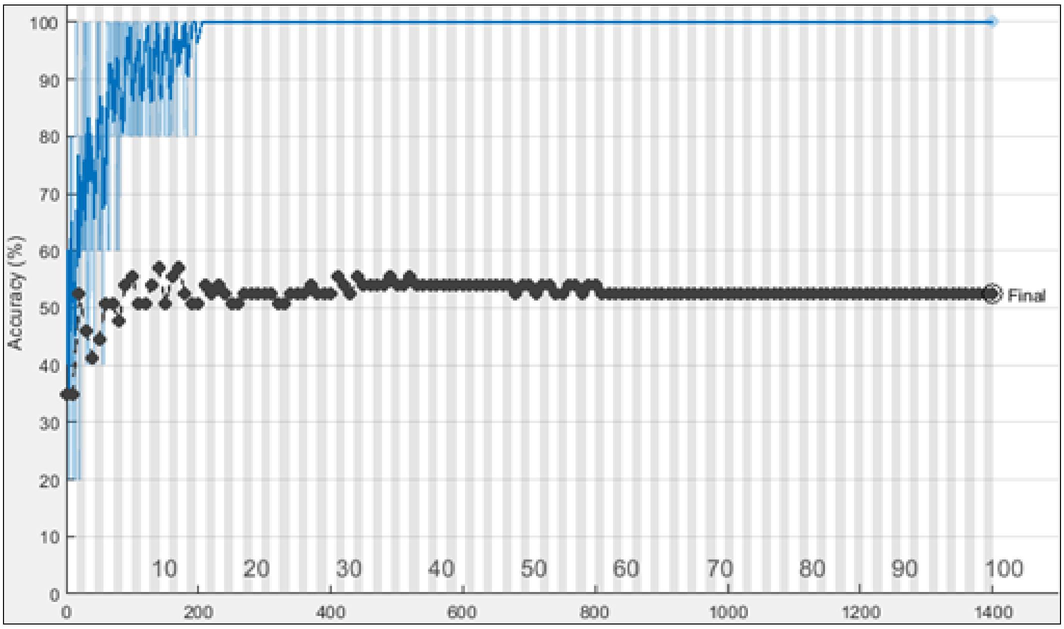


Fig 4: Evaluate the model on test data in Massive MIMO O-NOMA

Loss function as Fig 5 is a function used to assess the effectiveness of a machine learning model and quantify the discrepancy between predicted values and actual outcomes. The loss function aims to measure the extent to which the model's expectations agree with the actual data and guide the improvement process to reduce error. According to the loss function equation, we find that it varies according to the type of problem and the model. The user. There are many loss functions used in various machine learning applications. Below I will give some examples of common loss functions:

Mean squared error

It is used in problems that have continuous target values.

Loss equation:

$$L(y, \hat{y}) = \left(\frac{1}{N}\right) * \Sigma(y - \hat{y})^2 \quad (8)$$

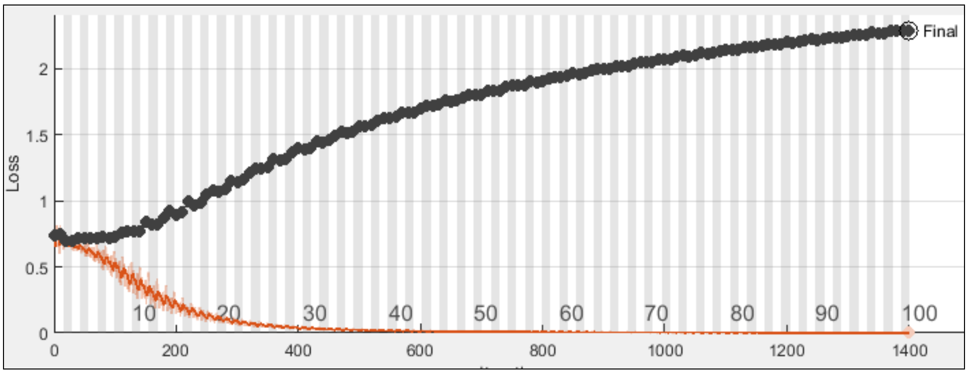
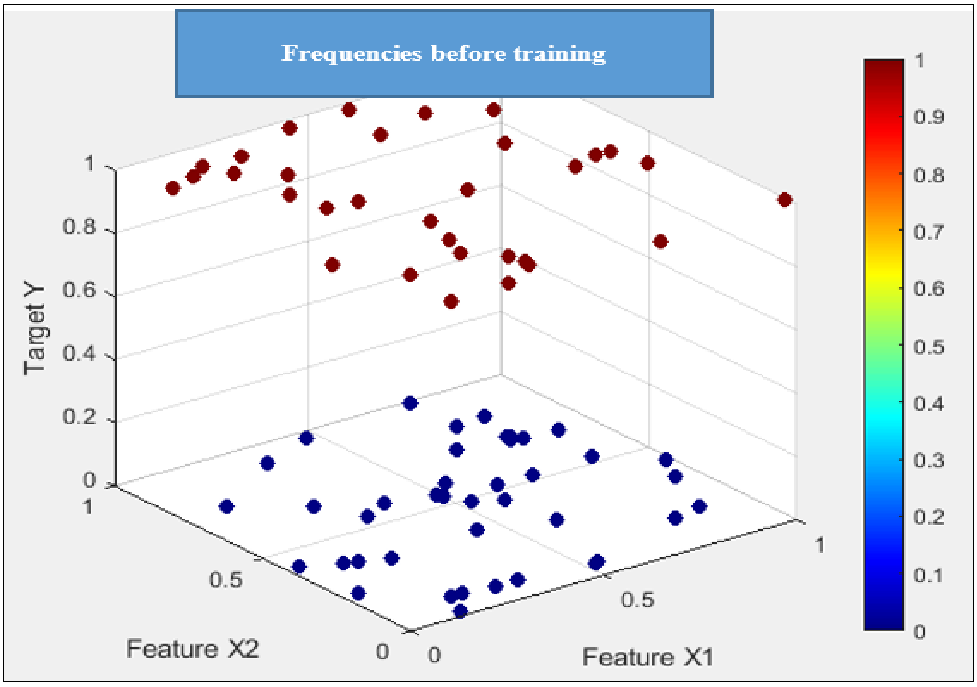


Fig 5: Loss function in Massive MIMO O-NOMA

Determine the frequencies of the data used in the system. Unique frequencies are assigned to each user and these frequencies are shared between different users. Since the data in the O-NOMA system is transmitted at the same time and on the same channel, the different frequencies allow different data to be distinguished from each other, but after training using... Deep Learning Techniques the performance of the detection process in the system is improved as deep learning models are trained on a large set of data collected from the system. These models are used to improve the detection and recognition process of data transmitted across different frequencies in the O-NOMA system, where frequencies play an important role. In improving the detection performance of Massive MIMO O-NOMA systems, by using different frequencies for each user in the O-NOMA system, different data can be individually distinguished and identified. This allows the system to analyze data sent across different frequencies and extract important information from them. By using O-NOMA technology and different frequencies, more data can be transmitted at the same time and on the same channel. This contributes to increasing transmission efficiency and improving energy use and thus prevents the interference process even if the frequencies are close to each other. We find it in the Fig 6. The performance of the detection process in the system can be improved. Models are trained to analyze data sent across different frequencies and identify them accurately, which leads to increased detection accuracy and improved overall system performance. Thus, with the use of different frequencies for each user and close together, interference between different data sent across the channel can be reduced, and this contributes to improving communication quality and reducing Data loss.



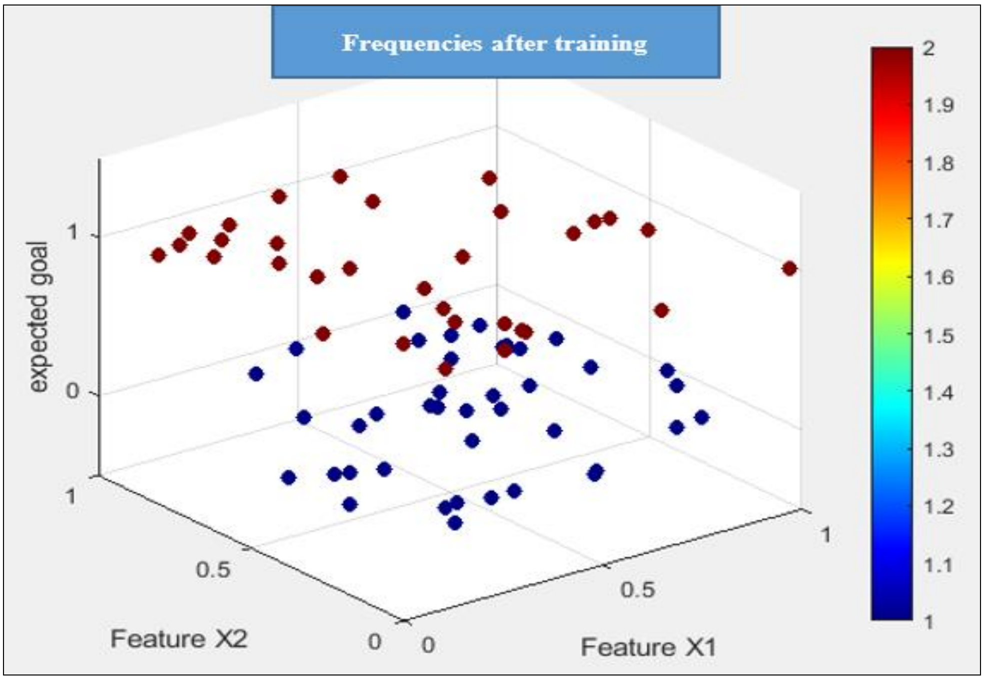


Fig 6: Frequencies before and after training

Conclusion

This study finds that the use of deep learning techniques in O-NOMA systems has the potential to enhance detection performance as deep neural networks allow overcoming the challenges facing traditional detection methods in these systems due to complex interference patterns and non-stationary channel conditions.

These methods rely on the advantages of deep neural networks to improve detection performance and enhance the ability to deal with complex and dynamic channel conditions. In addition, they deal with nonlinearity and interference, this makes them useful for M-MIMO-NOMA scenarios with lots of interference that enhance and user experience and spectrum efficiency and overall communication system performance.

Because distributed language model networks are created to make sense of conveyed symbols or decode information streams from processed incoming signal, as well as to process power allocation assignment coefficients and additional data, the process of regression optimization is employed to change network parameters in the course of training and also when tackling the deep learning issues in O-NOMA system.

Based on the results and recommendations from this study, deep learning techniques can be applied in O-NOMA systems to improve detection performance and increase spectrum efficiency and network capacity. Research in this area should also be continued to deal with additional challenges such as non-linear channel interference and non-stationarily varying channel conditions. Ultimately, this research can help in coming up with creative and efficient ways to improve detection performance in O-NOMA systems and make wireless communication more efficient in the time to come.

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