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**Research Article**

# Enhancing the features of 5G Communication using NOMA CRN ANN technologies

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**ABSTRACT**

There exist certain issues in the evolution of 5G communication systems, namely in terms of spectral-efficiency, latency, reliability, and security. Cognitive Radio Networks (CRNs) provide a remedy to the problem of resource scarcity in terms of spectrum sharing dynamics. While incorporating technologies such as MIMO and NOMA, it provides greater efficiency to the system but is bounded with interference levels affecting signal quality and security, specifically in MIMO-NOMA communication systems. Conventional methods of equalizers have limitations to maintain corresponding security levels among users, resulting in confidentiality concerns. This paper presents a wise approach using artificial neural network (ANN) solutions to offer improved physical-layer security to MIMO-NOMA communication systems in the context of Cognitive Radio Networks (CRNs). The proposed system treats multi-user interference and distortion related to channels, meeting power levels to provide improved performance towards increased security rate with decreased bit error rates despite the challenge in practical scenarios. An ANN-based equalizer has been implemented to achieve superior performance compared to conventional equalizer techniques (ZF, MMSE, and DFE) in terms of corresponding security levels with higher robustness towards practical scenarios with improved performance metrics with a score value at 94.95%. It clearly validates its benefits towards improving corresponding shared-spectrum 5G security and viability towards conventional technology solutions.

**Keywords:** 5G Communications, Cognitive Radio Networks, MIMO–NOMA, Physical Layer Security, Secrecy Rate, Artificial Neural Network, Intelligent Equalization, Interference Mitigation, Underlay Spectrum Sharing.

## INTRODUCTION

The ever-growing development of fifth generation (5G) and beyond wireless communication systems has imposed strict demands on spectral efficiency, reliability, latency, and security [1], [2]. Cognitive Radio Networks (CRNs) have recently been acknowledged as a promising technique to overcome spectrum scarcity issues with flexible dynamic spectrum sharing between primary (PUs) and secondary (SUs) users [3]. The further amalgamation of MIMO (Multiple-Input Multiple-Output) and NOMA (Non-Orthogonal Multiple Access) schemes with fifth generation 5G wireless communication systems with cognitive radio networks highly optimizes spectral efficiency and overall system throughput, making them very appropriate for future wireless communication systems [2], [6].

Despite such benefits provided by underlay spectrum sharing, it has been revealed in [4], [5] that underlying strict interference constraints to ensure PU protection significantly restrict the allowable transmission powers of SU and cause degradation of the signal quality and reliability. Such difficulties would be much exacerbated in MIMO-NOMA environments due to complex physical-layer processing involved in interference cancellation and increased threat of physical-layer security issues [6]. Additionally, various hardware and channel conditions, such as Doppler spread effects and carrier frequency-offset and phase noise effects, have been known to cause significant performance degradation of the system with high mobility and low SINR conditions [7]-[8].

Under these realistic transmission scenarios, traditional linear equalization methods, including Zero Forcing (ZF), Minimum Mean Square Error (MMSE), and Decision Feedback Equalizers (DFE), are unable to preserve an adequate signal-to-interference and noise ratio (SINR) margin between the desired parties and eavesdroppers in order to maintain an acceptable secrecy rate and prevent high secrecy outage probabilities, thus pointing to the critical deficiency of basic receiver designs in ensuring secure 5G cognitive radio transmissions.

With these challenges in mind, along with some recent breakthroughs in machine learning, a smart ANN-based equalization technique is proposed within this paper for improving the physics layer security of 5G MIMO-NOMA underlay cognitive radio networks in [9]. The proposed method will be capable of functioning under very limited interference conditions as well as power transmission constraints, taking into consideration practical hardware limitations of 5G communication, such as Doppler spread, CFO, phase noise, and more, in [7], [8]. Moreover, using ANN-based machine learning to effectively identify and remove MUI along with NL channel characteristics, a considerable improvement has been made in ANN-based equalizers concerning secret communication rate performance and BER compared to traditional equalizers, especially ZF, MMSE, DFE equalizers in terms of ANN-based machine learners in [9].

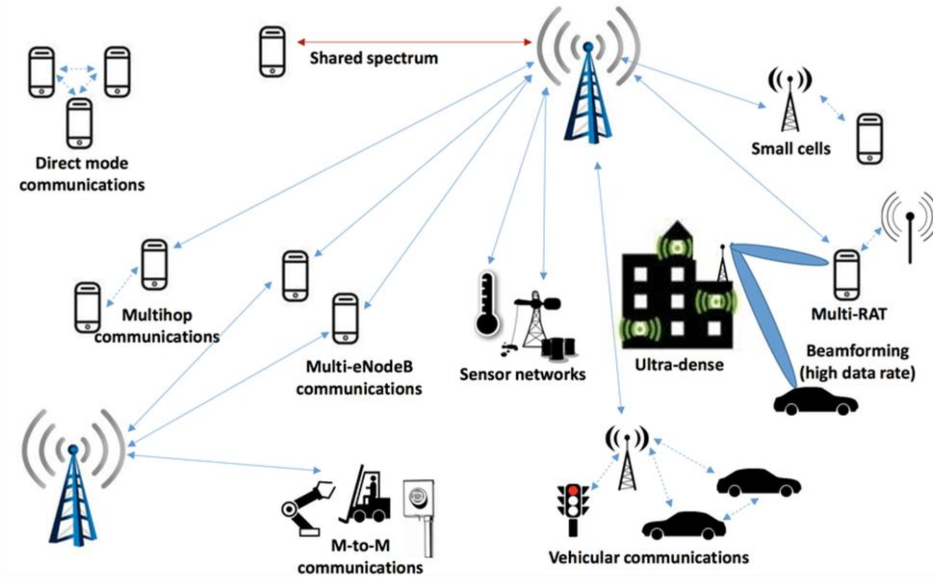

**Figure 1**: Beamforming technology used in 5G networks

## OBJECTIVES

The objective of this paper is to develop an intelligent ANN-based equalization framework for enhancing physical-layer security in 5G MIMO–NOMA underlay cognitive radio networks. The proposed approach aims to mitigate multi-user interference and nonlinear channel impairments while operating under strict power and interference constraints. By learning complex channel characteristics, the framework seeks to improve secrecy rate, maintain a sufficient SINR gap between legitimate users and eavesdroppers, and reduce bit error rate in the presence of practical impairments such as Doppler spread, carrier frequency offset, and phase noise. Extensive simulations are conducted to benchmark the proposed method against conventional linear equalizers and to validate its robustness and effectiveness under realistic 5G operating conditions.

## LITERATURE REVIEW

Reddy et al. (2020) presented the INTERSPEECH Challenge on Deep Noise Suppression to promote real-time single-channel DNS using deep learning. The paper pointed out the insufficiency of common objective evaluation and the model performance deterioration caused by real conditions after synthetic data-based learning. The contribution of this work lies in providing open-source data and a more accurate ITU-T P.808-based subjective assessment. The contribution of this work is to show that data-driven learning and objective assessment are crucial. As a speech enhancement technique not relevant to wireless communication systems but highly related to equalization for interference-dominated wireless communication systems using ANN equalization technology [10], this work proves the efficacy of using deep learning to learn complex noise characteristics.

Lee et al. (2020) designed an on-off cooperative phase steering (CPS) method to improve wireless sensor networks with on-off power control support for cooperative spectra sharing. Theoretical values were calculated to show that CPS is more efficient than cooperative communication methods. However, this paper focuses on cognitive wireless sensor networks with interference environments but does not include physical-layer-based secure communication systems without MIMO and NOMA communication systems or receiver-side equalization intelligence treatments either [11].

Guo et al. (2024) explored discrete phase control-based physical-layer cryptography for cognitive RIS-aided networks. Theoretical expressions for secrecy outage probabilities were given. Results show that using RIS can promote physical-layer confidentiality. However, this paper is based on signal propagation and does not consider real receiver-side problems such as multi-user interference or learning-based equalization strategies either [12].

Wang, et al. (2024) tackled the signal detection problem in MIMO-NOMA systems by designing a feedback deep neural network receiver to replace the conventional successive interference cancellation receiver. By leveraging the non-linear signal detection capabilities of deep learning, the designed feedback deep neural network receiver achieved a considerable decrease in bit error rate and corrected the error propagation effects that were naturally incurred in the conventional successive interference cancellation receiver. Although the above work verifies the effectiveness of deep learning networks for interference mitigation in the MIMO-NOMA network, the work has not taken into account the physical layer security criteria, the physical layer security metrics, and the secrecy rate calculation [13].

Saravanan, et al. (2025) designed a secure channel estimation model based on deep learning and channel state information in cognitive radio networks for improving the physical layer security levels. In their estimation, the carefully designed physical layer security system included the implementation of beamforming techniques, along with the addition of a two-level authentication process, to ensure a better secrecy rate value along with less interference. Although the designed physical layer security system has obtained considerable secrecy gains, the estimation was based on the channel estimation and the authentication processes, without giving much priority to the receiver equalization process, and the effect of the resulting interference in the NOMA systems was not addressed by the proposed physical layer security solution [14].

Wang, et al. (2025) designed a deep learning network named a Multiple Input Multiple Output Neural Network (MIMO-NN) combined with Batch-wise Decision-Directed Phase Recovery Algorithm (BDDPR) for utilizing the deep learning networks in coherent optical communication systems at a faster data rate. By combining the phase noise recovery capabilities of the BDDPR algorithm and the neural networks, the designed solution significantly lessened the increased signal processing delay. By experimenting the design with a PDM-16QAM optical coherent communication system at a significantly increased data rate, the researchers have concluded that the BDDPR combined with the designed neural networks can achieve considerable sensitivity improvement and a considerable reduction in the complexity compared to the conventional signal processing techniques in optical communication systems. Although the designed solution has presented the effect of phase noise on the deep learning-based signal equalization, the designed solution has been limited within the optical coherent communication system, and the effects due to various channels, the effects due to the cognitive radio networks, the interference due to the NOMA networks, and the physical layer security criteria such as the secrecy rate were not addressed by the designed solution [15].

Wang, et al. (2025) analyzed the speech enhancement problem utilizing the attentions paid by the receiver within deep learning networks. By carefully analyzing the effects due to the window sizes, the effects due to the loss, and the effects due to the representation, the authors concluded that the deep learning networks can pay considerable attention to the complex noise and distortion effects, resulting in a superior performance compared to the conventional speech enhancement techniques [16]. Despite the current research being on audio signal processing and not on wireless communication systems, it is relevant evidence regarding the ability of deep artificial neural networks to recover nonlinear signals in a noisy environment. This supports theoretically the use of artificial neural networks in the equalization process in secure wireless communication systems. [16]

Previous research has explored the issue of secure/efficient communications from various angles, but not together like in this proposed research, where multi-user interference, spectrum sharing, NOMA constraints, as well as hardware impairments of the cognitive radio, are considered. Though deep learning has led to the improvement of signal detection performance in the non-wireless/MIMO-NOMA communications, these approaches have not considered the limitations of the cognitive radio, receiver-side equalization, or secrecy problem optimization. This proposed research, on the other hand, blends ANN-based equalization techniques for the first time with the physical layer of secrecy for a 5G MIMO-NOMA underlay cognitive radio network and hence fulfills a research gap.

## METHODS

A downlink 5G MIMO–NOMA underlay cognitive radio system is considered, where multiple secondary users communicate in the presence of a primary receiver subject to interference temperature constraints. The system model incorporates realistic channel impairments, including multipath fading, Doppler effects, CFO, and phase noise. The proposed ANN-based equalizer is trained using large synthetic datasets generated over a wide range of channel realizations, Eb/N0 values, and interference scenarios. The ANN learns the nonlinear mapping between the received signal vectors and the transmitted symbols, enabling robust symbol reconstruction. For performance comparison, classical equalizers—ZF, MMSE, and DFE—are implemented as benchmark schemes. Key performance metrics include secrecy rate, BER, SINR gap between legitimate users and eavesdroppers, and robustness under hardware and mobility-induced impairments.

### Optimization of Congestive Radio Networks (CRNs)

With the increasing demand for spectrally efficient communications, Cognitive Radio (CR) has emerged as a key solution for dynamic spectrum access by sensing and adapting to the RF environment. Introduced by Mitola, CR has gained strong interest from the FCC to mitigate spectrum scarcity and access conflicts. Traditional spectrum sensing methods, particularly energy detection, are simple but highly sensitive to interference and noise and cannot distinguish between different signal types. Conventional signal classification approaches rely on handcrafted features and model-based decision techniques, often requiring prior signal knowledge. More advanced methods, such as those based on higher-order statistics, have improved modulation classification but still face challenges under unknown carrier frequencies and modulation rates. To overcome these limitations, this work revisits signal classification from a spectral connectivity perspective and proposes neural network–based classification with appropriate preprocessing, demonstrating robustness against interference and noise [17].

Congestive Radio Networks is an intelligent network that allow wireless devices to dynamically utilize unused radio spectrum (spectrum holes) in a safe and non-disruptive manner for authorized primary users. The goal is to improve spectrum utilization efficiency, support diverse services, and enable flexible communications in changing environments. The core concept of CRN is to allocate fixed spectrum to each service. Secondary users then use their awareness to sense the spectrum, identify unused spectrum, and decide when and at what power and frequency to broadcast, while ensuring no harmful interference occurs to primary users. Spectrum sensing methods operate within certain limitations:

#### 1. Energy Detection

- The simplest method: compares signal energy to a threshold level.
- Advantages: simple, no reference signal required.
- Disadvantages: sensitive to noise, performance decreases at low SNR, does not distinguish signal type.
- Test: $T = \sum_{n=1}^{N} |[n]r|^2$ → Compare to \lambda.

- Important indicators: Detection probability $P_d$ and false alarm probability $P_{fa}$.

#### 2. Matched Filter Detection

- Optimized if you have prior knowledge of the primary user's signal type.

- Faster and more accurate, but requires synchronization and knowledge of the signal shape.

### 3. Cyclostationary Feature Detection

- Exploits periodic characteristics in the signal to distinguish it from noise.
- More powerful against noise but more computationally complex.

### 4. Cooperative Sensing

- Combines decisions or metrics from multiple nodes to overcome problems such as hidden nodes.
- Improves $P_d$ and reduces $P_{fa}$, but requires timing and information sharing.

The role of technology in conjunction with artificial intelligence and machine learning can be summarized as follows:

a) Spectrum Occupancy Prediction: Time-based models (RNN, LSTM) or statistical models to predict free spectrum opportunities.

b) Sensing Strategy Improvement: Reducing sensing time through reinforcement learning policies to select the best channels.

c) Classification: Using neural networks to detect signal types and distinguish them from noise.

d) Adaptive Control: Dynamically adjusting power and beamforming to balance throughput and interference.

In summary, cognitive radio networks (CRNs) offer a flexible and intelligent framework for more efficient use of the radio spectrum through accurate spectrum sensing, dynamic channel and power selection decisions, and secure spectrum sharing while protecting the primary user. The practical success of CRNs depends on the quality of sensing, collaborative strategies, interference controls, and the use of artificial intelligence techniques to optimize dynamic decision-making.

## Single-Input, Single-Output (SISO System)

Over the past several years—particularly the last decade—the communications industry has witnessed remarkable growth, driving people to adopt advancements in mobile technology at an unprecedented pace. Mobile communication has evolved from 2G to 4G, with data rates progressing from approximately 12 kbps in 2G to around 2 Mbps in 3G, and further to downlink speeds of up to 100 Mbps and uplink speeds of 50 Mbps in 4G-LTE [18].

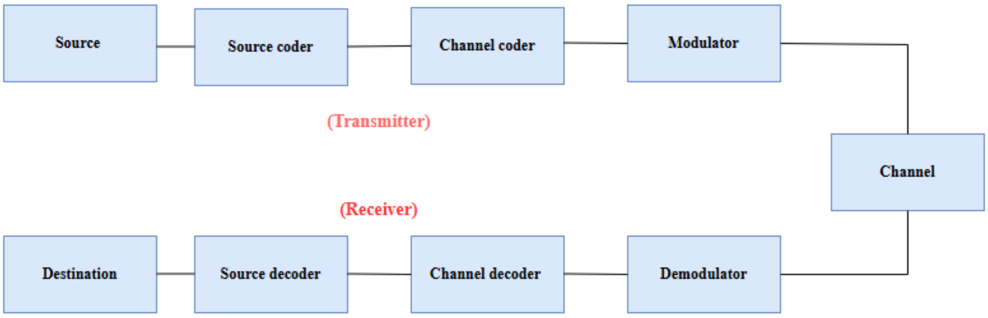

**Figure 2**: Block Diagram of wireless digital communication system with SISO channel [18].

The block diagram above illustrates how signals are transmitted and received over radio channels. In this diagram, the transmitting antenna is placed after the modulator to deliver the modulated signal through the radio channel to the receiving antenna. The quality of the signal received depends heavily on the characteristics of the channel, as various unwanted signals or noise can be introduced during transmission from the sender to the receiver. Antennas are positioned at both ends to facilitate signal transmission, and the system's channel capacity is influenced by the types of antennas used [19]. In a single-input single-output (SISO) system, there is one antenna at the transmitter

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and one at the receiver. This configuration is the simplest and easiest to implement among all antenna types. Figure 2 presents the block diagram of a SISO system.

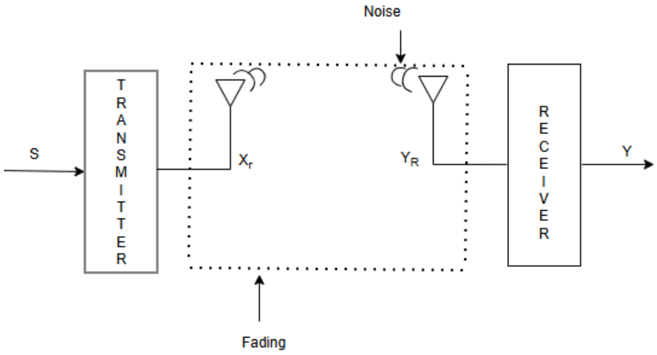

**Figure 3**: Block diagram of the SISO System.

In the previous diagram, S represents the input, Y the output, XT the transmitting antenna, and YR the receiving antenna. Noise is introduced into the system during the transmission of the waveform from XT to YR, and the waveform may fluctuate or distort during this process, as illustrated in the diagram. The channel capacity of the SISO system is defined as [20]:

$$C_{SISO} = BLog_2(1 + \frac{S}{N}) \tag{1}$$

In this expression, C represents the channel capacity, B is the bandwidth of the waveform, and S/N denotes the signal-to-noise ratio (SNR). The transmission capacity of a SISO system is constrained by Shannon's Law, which defines the theoretical maximum rate at which error-free data can be transmitted over a bandwidth-limited channel in the presence of noise. The primary advantage of using a SISO system lies in its simplicity and low cost, making it more affordable than other communication system types. SISO systems are commonly used in applications such as Wi-Fi, television, and radio broadcasting [20].

## Classical Equalizer Techniques

In wireless communication systems, the goal of an equalizer is to reverse the effects of multipath channels and time-spectral nonlinearity (ISI), as well as to handle spatial interference (in the case of MIMO), so that the transmitted code is recovered with the least possible error. There are several equalization methods; we will focus on comparing the three most important ones with the deep learning technique proposed in our system: Zero-Forcing (ZF), MMSE, and DFE [21].

In ZF, the channel represents a linear process affecting the transmitted signal: the received signal becomes H · x + n (where H is the channel matrix or the channel's pulse response signal, x is the code, and n is the noise).

The goal of an equalizer is to select a filter (matrix or filter) W to be applied to the received signal to produce an estimate of Δx = W Δy, such that the error is small according to a specific criterion (e.g., interference cancellation or minimizing the mean squared error). The difference between the methods lies in the design criteria (complete interference cancellation, a balance between interference cancellation and noise reduction, or the use of feedback decisions).

### 3.1 Zero-Forcing (ZF)

The basic idea: to completely eliminate channel interference (eliminating ISI or micro-symbol/current interference) so that the system becomes "live" without considering noise. The most important advantage of this technique is its simplicity and clarity in both concept and implementation. It also eliminates interference caused by multipath or space interference in MIMO [22]. However, the main disadvantage of the technique is noise enhancement: if H contains small singularity values (weak/near singularity channel), the inversion process greatly amplifies the noise, thus degrading the BER performance. It also requires precise channel estimation and is not ideal under low SNR conditions.

for the Zero Forcing (ZF) detector to satisfy this condition, Equation (3) can be expressed as:

$$W = (H^{2}H)\text{-}1\ H^{H} \tag{2}$$

Were

W - Equalization Matrix, also H - Channel Matrix. Such a matrix is defined as the pseudo-inverse for a general m × n matrix.

It is important to note that the off-diagonal elements in the matrix H are not zero. Because of these non-zero off-diagonal terms, the Zero Forcing (ZF) equalizer attempts to cancel out the interference between transmitted symbols during equalization. For instance, when solving for x1, the interference from x2 is suppressed, and vice versa. However, this interference cancellation can lead to noise amplification, which is a significant drawback. As a result, the Zero Forcing equalizer is not the most optimal solution in terms of performance, though it remains a simple and relatively easy method to implement. Furthermore, after applying Zero Forcing equalization, the channel associated with each transmitted symbol (from each spatial stream or antenna) resembles a 1×1 Rayleigh fading channel. For Binary Phase Shift Keying (BPSK) modulation in such a Rayleigh fading environment, the bit error rate (BER) is given by:

$$P_d = \frac{1}{2}\left(1 - \sqrt{\frac{\frac{E_b}{N_o}}{\left(\frac{E_b}{N_o}\right)+1}}\right) \tag{3}$$

Were

b - Bit Error Rate

$\frac{E_b}{N_o}$ - Signal to Noise Ratio

### 3.2 Minimum Mean Square Error (MMSE)

The basic idea: Balancing interference cancellation and noise reduction. Instead of completely canceling interference regardless of noise (as in ZF), MMSE reduces the average squared error between the actual symbols and their estimates, taking noise into account. The working principle is as follows [23]:

- The designer looks for W that minimizes E $[\|X - W_y\|^2]$.
- For the known linear case, the MMSE solution is in matrix form:

$$W_{MMSE} = (\ H^H\ H + \sigma_n^2\ I)^{-1}\ H^H \tag{4}$$

where:

- $H^H$ denotes the Hermitian (conjugate transpose) of the channel matrix H\mathbf{H}H,
- $\sigma_n^2$ represents the noise variance (or equivalently $N_0/E_s$ in alternative formulations),
- I is the identity matrix.

We observe that when the noise is very small (σ→0), MMSE becomes close to ZF, and when the noise is large, it acts as a filter that reduces amplification for weak directions. The most important advantage of this technique is reducing the effect of noise amplification compared to ZF. BER typically offers better performance, especially at medium and low SNRs, and is more flexible because it balances interference cancellation and noise reduction.

However, the main drawback of the technology is its computational complexity, and it doesn't guarantee complete interference cancellation, which is sometimes required for certain strategies (for example, in some MIMO applications with advanced technologies).

### Decision Feedback Equalizer (DFE)

The core idea behind DFE is to utilize previous decisions (estimated symbols) to cancel the trace effect of those earlier symbols on the current ones, thus reducing ISI in a way that is less susceptible to noise than simple linear solutions. The DFE architecture consists of two parts: a feed-forward filter (FFF) that processes noise and components coming from the channel, and a feedback filter (FBF) that uses previous decisions to cancel the remaining ISI. After applying the FFF to the incoming signal, an initial estimation is obtained. Hard or soft decisions are then made on the symbols, and finally, the FBF is applied to remove the contribution of the determined symbols from the incoming signal before a new decision is made. Therefore, the most important advantage of this technique is that it effectively reduces ISI without amplifying noise, unlike ZF, because the cancellation part is achieved through feedback (it does not involve reflecting the weak spectrum in the same way). It also offers better performance than linear disadvantages (ZF/MMSE) in powerful multipath channels (high ISI). It is more efficient in spectrum utilization than a linear equalizer of the same complexity in many cases. However, the most significant drawback is error propagation: if an incorrect decision is made at any stage, this error can be exploited later in the FBF and may cause a chain reaction of errors that negatively impacts performance. This is the primary risk of DFE. Additionally, it may not be suitable if the encoding system is weak or if the channel variables are too fast (adaptation delay) [24].

### 3.4 Multiple Input Multiple Output (MIMO) technology

Is one of the most important engineering pillars that has allowed for a significant increase in the performance of wireless networks, especially in 5G networks. The basic idea is based on using multiple transmitting antennas and multiple receiving antennas to increase capacity, reduce interference, and improve connection reliability. The mathematical basis and core concept: In a traditional SISO (Switched-to-Switch) system, the signal travels from one antenna to another. In MIMO, however, the signal is divided into several independent streams that are transmitted through multiple antennas [25]. The basic equation is: $y = H/x + n$

Where: x: Transmitted signal vector, H: Channel matrix, y: Received signal vector, n: Noise.

The Rank(H) value determines the number of “independent paths” the system can use, which is the basis of MIMO’s capacity-doubling advantage.

The most important types of MIMO technology are:

#### 1- Spatial Multiplexing

The most important and widely used MIMO technology is in 4G/5G. Several independent streams are transmitted simultaneously through different antennas. If we have 4x4 MIMO, four independent streams can be transmitted, resulting in approximately a fourfold increase in speed. This principle is what allowed for a huge leap in throughput [26].

#### 2- Beamforming

A technology that makes the transmitting antennas act as a smart array, forming a coherent beam directed towards the user. Its advantages include increased signal strength for the user, reduced interference, and improved power efficiency [27].

#### 3- Massive MIMO

Is the most important element developed in within 5G. The fifth generation relied on a new leap: a massive increase in the number of antennas on towers, reaching 64 antennas, 128 antennas, and 256 antennas. increasing the number of antennas increases the rank(H), allowing for a greater number of independent paths (spatial streams). This leads to a huge jump in throughput, exceeding 10x compared to 4G. Furthermore, a large number of antennas allows for the formation of very precise, narrow beams targeting a single user. The result is stronger coverage, reduced interference, and lower power consumption [28].

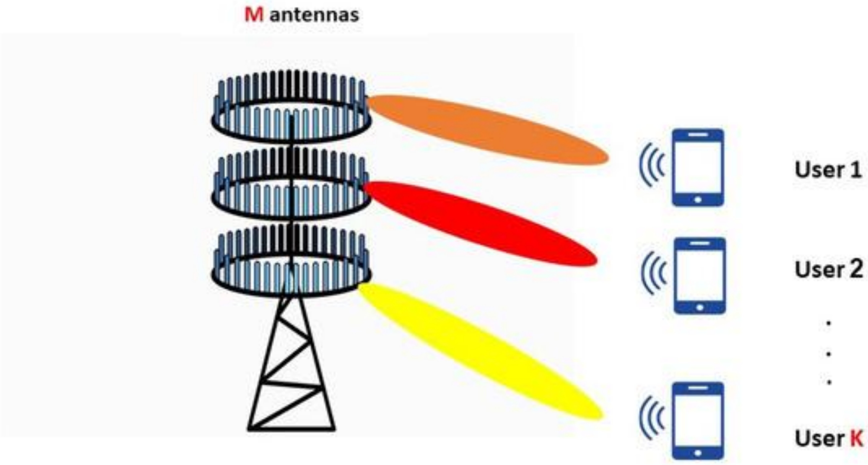

**Figure 4**: massive MIMO system

## NOMA (Non-Orthogonal Multiple Access) technology

Is a modern approach in 5G and beyond networks, aiming to increase the efficiency of wireless resource utilization and overall network capacity. It allows multiple users to access the same resource at the same time and frequency in a non-orthogonal manner by combining their signals into a single channel using Power Domain Multiplexing (PDM). This differs from traditional methods that separate users based on time or frequency. The base station transmits signals to multiple users simultaneously on the same resource (same frequency, same time), but it adjusts the transmission power for each user according to their channel strength [29]:

- Users on weaker channels receive higher power.
- Users on stronger channels receive lower power.

The reason for this is to allow users on weaker channels to receive their signal more clearly amidst interference. At the receivers, the interference is removed sequentially:

- Users on stronger channels can first separate the high-power signal, then subtract it from the received signal, and finally extract their own signal.
- Users on weaker channels do not need to do this because they already receive a higher-powered signal. This process is called cascade interference cancellation and is the cornerstone of NOMA's success.

The importance of NOMA technology lies in the following points:

1. Increasing overall network capacity by operating two or more users on the same resource, spectrum utilization efficiency is doubled.
2. Improving fairness Variable capacity technology helps serve users far from the base station without significantly impacting those with good channel access.
3. Supporting a larger number of users This is essential for 5G and beyond networks due to high-traffic scenarios (such as IoT).

Its practical applications lie in 5G networks, particularly in small-cell scenarios and high-density user support. It is also used for connecting multiple devices in the Internet of Things (IoT). Furthermore, it is used in long-range communications with significant channel quality variations.

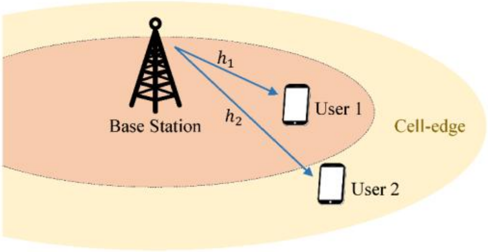

**Figure 5**: Illustration of downlink non-orthogonal multiple access

## Artificial Neural Network (ANN)

It is a mathematical models inspired by the workings of the human brain. They are used to process data, learn from experience, extract patterns, and make predictions. They form the basis of most modern artificial intelligence technologies, including computer vision, speech recognition, and big data analytics. An ANN relies on a set of "nodes" called neurons, which function in a simplified manner similar to neurons in the brain. Each node receives data, performs a simple mathematical operation on it, and then sends the result to the next node. These simple operations, when combined into a large network, lead to complex capabilities such as image recognition or time series prediction. The basic structure of a neural network consists of [30]:

**Input Layer:** This layer receives raw data (images, text, audio, numbers, etc.).

**Hidden Layers:** These are the backbone of the network. They learn from the data through mathematical transformations called Activation Functions, which help the network understand complex patterns. Each hidden layer contains several neurons and is connected to the next layer by a series of weights.

**Output Layer:** Produces the decision or prediction, such as classifying an image or giving the probability of a certain event.

ANN technology learns through a process called backpropagation, which is at the heart of the technology. Its basic steps are:

A) Forward Pass: Inputting data from the first layer to the last to obtain an initial output.

B) Loss Function, Such as MSE or Cross-Entropy, to determine the accuracy of the network.

C) Backward Pass The network goes back through the layers to adjust the weights and reduce the error.

D) Optimization. This is done using algorithms such as Gradient Descent, ADAM, and RMSProp. This process is repeated thousands of times until the network learns the required patterns.

Thus, ANN technology is a computational model composed of interconnected layers of nodes that learns the relationship between inputs and outputs by adjusting weights in a way that minimizes error. It is the cornerstone of deep learning and modern artificial intelligence.

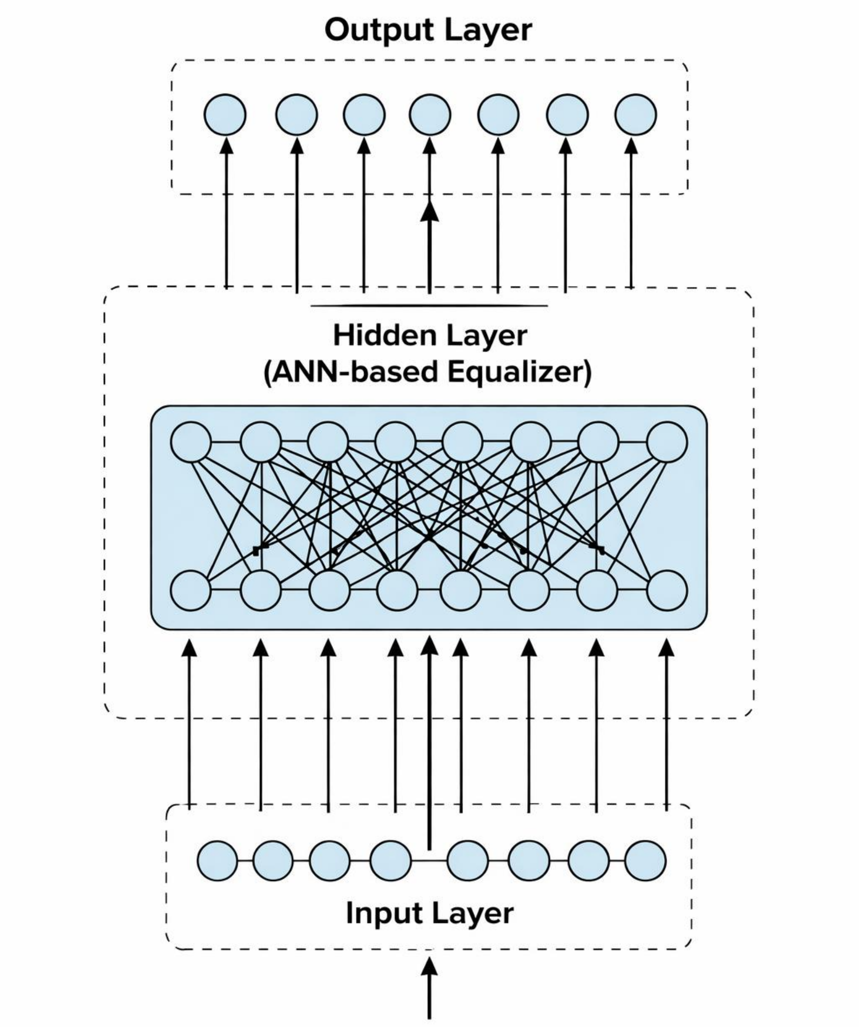

**Figure 6**: The simulation structure of the proposed ANN equalizer model using MATLAB Simulink

## RESULTS

### Proposed ANN Controller Model

The central intelligence in this proposed secrecy-oriented architecture is the controller, which, as stated above, is based on an artificial neural network and acts as a nonlinear equalizer and symbol reconstruction component at the receiving end. In this case, instead of using linear filtering methods, this controller learns a nonlinear mapping between the distorted transmission signals, the estimated MIMO channels, and QPSK symbols while taking into consideration the effects of NOMA and cognitive radio environments.

For each OFDM data subcarrier, a feature vector expressing a set of concise channel characteristics, which consists of the real and imaginary parts of the signals received through multiple antennas, as well as corresponding effective channel coefficients, is processed by the controller. This enables modeling by a neural network without any need to specify models for interference, channel fades, and hardware imperfections.

The controller is implemented using a fully connected deep neural network with four hidden layers and dropout for regularization. ReLU activation functions are used in all hidden layers, and a linear activation function with two neurons is used in the output layer to provide a direct estimation of the real and imaginary parts of the equalized symbol. The network is trained in an offline mode using a supervised learning approach with a substantial amount of simulated signal patterns covering a broad range of Eb/N0 values, different channel conditions, and various underlay interference environments. The network parameters are updated using mean squared error between the estimated and actual symbol components with the AdamW optimizer, assisted with a learning rate schedule that involves a warm-up stage followed by cosine annealing.

After that, the ANN-based controller is inserted into the receiver chain as a valid user as well as at the eavesdropper node to compare the result, and its symbol estimates are further fed into the NOMA-SIC module. In this regard, not only is the bit error rate reduced, but also it increases the secrecy rate indirectly since it boosts the channels for legitimate users more compared to those at eavesdroppers.

## Training and Validation Process

The training and testing of the equalizer based on the ANN model are conducted solely in the context of the supervised learning model on the artificial data generated from the aforementioned 5G MIMO-NOMA cognitive radio scenario. In the training phase, the model generates random OFDM symbols indefinitely across a wide range of Eb/N0, introducing fresh channel conditions, patterns of the superposed NOMA signal, and underlay interference.

For every incoming OFDM signal, the disturbed symbol values and their corresponding effective MIMO channel values are fed as feature vectors, and the real and imaginary components of original QPSK symbols are taken as targets. This naturally ensures that the network observes a multitude of channel conditions, which in turn helps it to learn robustly.

The optimizer is designed to be stable during optimization by using 300 epochs of training with the "AdamW" optimizer with weight decay regularization. The learning rate schedule is a two-step plan consisting of a linear warming-up period to avoid instabilities in the early stages, followed by a cosine annealing learning rate schedule to allow a smooth optimization of parameters. The performance metrics are computed by taking an average of all SNR values at the end of each epoch with random sampling of the data fed in a mini-batch size of 8192. The loss function used during the learning process is the average squared error between the estimated symbol components and actual symbol components.

The validation occurs implicitly by observing the evolution of the MSE for the entireepoch and by comparing the performance of the trained system with the standard ZF, MMSE, and DFE equalizers. There is no need to have a separate validation data set because, during each epoch, different random channel and noise conditions are introduced, which virtually constitutes an endless and non-repeating data source. The training procedure is deemed complete when the MSE converges and the performance of the trained ANN-based equalizer is always superior to the linear methods for secrecy rate and BER performance analysis.

## Evaluation Metrics

To assess the performance of the proposed ANN-based equalizer, an adapted set of performance metrics is used in comparison with a traditional receiver; the criteria involved are related to detection, secrecy, link quality, robustness, and Cognitive Radio constraints.

1. Eb/N0 and Noise Scaling

The analysis uses Eb/N0 rather than just SNR. Each data point, a certain Eb/N0 sets the noise variance for the AWGN channel in the system; this is standard when considering secrecy and error performance in digital communications.

2. Bit Error Rate (BER)

BER measures the fraction of the number of bits detected wrongly, out of the total transmitted bits. This allows separate BER calculation for the SIC (for strong users) and non-SIC case, whereby strong users will employ Successive Interference Cancellation. This will provide the exact test for data recovery across various equalization techniques under interference and noise from NOMA.

3. Signal to Interference plus Noise Ratio (SINR)

The SINR reflects the true quality of the equalized channel and hence tells how effectively multi-user interference and noise has been suppressed. The derivation of the SINR from the accurate symbol reconstruction thus allows making a comparison between the performances of LE and ANN.

4. Secrecy Rate (Rs)

The secrecy rate is defined as the difference between the maximum information rate achievable in the legitimate channel and that in the eavesdropper's channel. A higher secrecy rate means the intended receiver can decode more reliably than an eavesdropper. This secrecy rate is the primary performance metric of the system.

5. Secrecy Gain

Secrecy Gain Secrecy gain quantifies the improvement of secrecy rates of the ANN equalizer compared to a baseline linear method, such as MMSE. It directly gives the amount of more secure information the ANN can support, especially for low and medium Eb/N0 values.

6. Secrecy Outage Probability (SOP)

It gives the probability that the achieved secrecy rate is less than the target secrecy rate. The smaller the outage probability is, the better the secrecy performance will be.

7. Cognitive-Radio Interference Compliance

In underlay cognitive radio configurations, the interference at the primary user should remain below a threshold, which characterizes the efficiency in controlling transmit power.

8. Robustness Metric

The robustness is tested against impairments that the channel may introduce, in terms of Doppler shifts, carrier frequency offset, and phase noise, with respect to the secrecy rate and BER. It's demonstrated that the ANN equalizer retains its advantages even when it takes into consideration the effects of Doppler.

## Simulation Results

Performance outcomes may be considered as a function of translating what's in the content into something measurable in terms of performance, all in an environment characterized by a high degree of secrecy, as identified in the operation modes. Figure 7 plots the performance in training the ANN model in 300 epochs, focusing on the considerable drop in MSE in the early stages. Commencing from an MSE lower than 0.50 in epoch 1, it significantly reduces to approximately 0.44 by epoch 10, thus projecting a highly encouraging performance trend. However, as training progresses beyond the 30-40 epochs mark, the trends undergo a marked shift in which the performance stabilizes in a particular zone with minimal MSE variations within the 0.433-0.438 region.

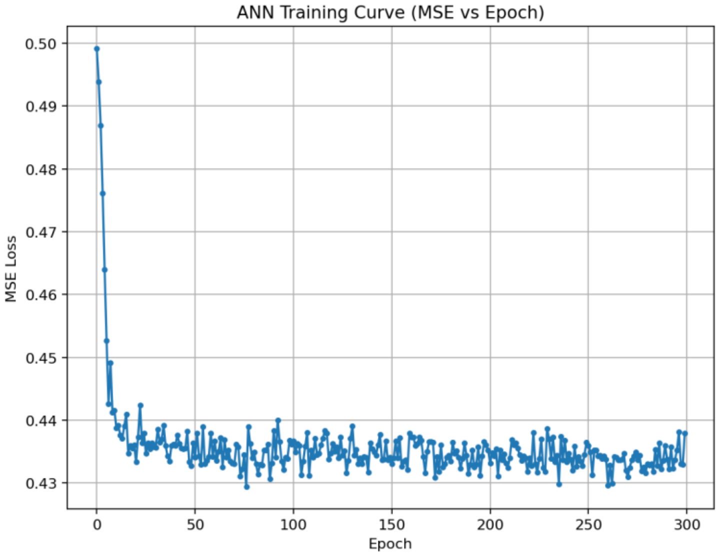

**Figure 7**: ANN Training Curve

**Table 1**: Selected MSE Values During Training

| Epoch Range | Training MSE (approx.) |
|---|---|
| **1** | 0.498 |
| **10** | 0.445 |
| **50** | 0.436 |
| **100** | 0.434 |
| **200** | 0.433 |
| **300** | 0.434 |

From Table 1 above, convergence of the ANN is evident through the MSE values: approximately 0.498 at epoch 1, 0.446 at epoch 10, 0.436 at epoch 50, and converging to 0.434 at epoch 100 through epoch 300. These values confirm the model of secrecy behavior of the system under observation. A properly trained equalizer will enhance the reconstruction of the legal users' symbol and will produce a performance gap with the eavesdroppers' channel. The true scenario will become clearer in the following figures, especially upon observation of secrecy rates in Figure 8 below.

On the other hand, the traditional equalizers, such as ZF, MMSE, and DFE, achieve secrecy rates that remain close to zero for all Eb/N0 regions. The reason for their deterioration in performance could be the interference caused by NOMA, the power constraint due to cognitive radio, and the nonlinear nature inherent in the MIMO-OFDM channel. For the maximum Eb/N0 region, their secrecy rate remains below 0.015-bit/s/Hz.

Compared to the above, the secrecy rate improvement of the ANN equalizer is noticeable as the Eb/N0 increases. From a secrecy rate of 0.024-bit/s/Hz at Eb/N0 of -5 dB, progressing to 0.060-bit/s/Hz at Eb/N0 of 0 dB, and then to 0.077-bit/s/Hz at Eb/N0 of 5 dB, and finally breaking the threshold of 0.10-bit/s/Hz between Eb/N0.

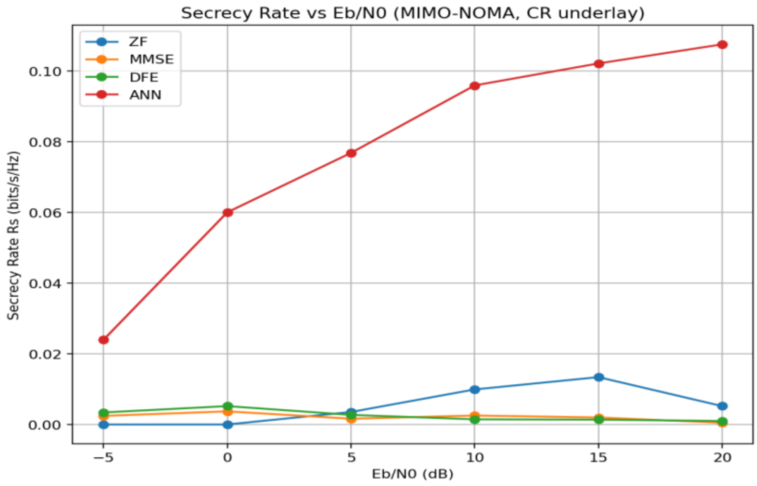

**Figure 8**: Secrecy Rate vs Eb/N0

**Table 2:** Secrecy Rate Values

| Eb/N0 (dB) | ZF | MMSE | DFE | ANN |
|---|---|---|---|---|
| **-5** | 0.000 | 0.002 | 0.003 | 0.024 |
| **0** | 0.000 | 0.003 | 0.005 | 0.060 |
| **5** | 0.004 | 0.002 | 0.002 | 0.077 |
| **10** | 0.010 | 0.002 | 0.001 | 0.095 |

| | | | | |
|---|---|---|---|---|
| **15** | 0.013 | 0.002 | 0.001 | 0.102 |
| **20** | 0.005 | 0.001 | 0.000 | 0.108 |

From Table 2, it's evident that the ANN offers secrecy-rate performance that far excites other linear techniques by more than an order of magnitude. This trend justifies the main objective of this research work. The ANN, with its non-linear learning process, proves to demonstrate its ability to resist interference that accompanies NOMA. It proves its effectiveness to enable legitimate users to recover symbols with significantly higher accuracy, which in return manifests the significant difference in the received SINR among legitimate users and potential eavesdroppers. The close relationship among the stable values of MSE in Figure 8 and improvements in secrecy rates in Figure 6 reflects that the ANN equalizer is not well-trained, although it remains dynamically engaged to promote physical-layer security in real-world 5G MIMO-NOMA-CR systems. The simulation outcome has exclusively concentrated on demonstrating the performance of the newly developed Artificial Neural Network Equalizer at cognitive radio networks. The outcome has also described how it affects Bit-Error Rates in Weak and Strong NOMA users.

Figure 8 shows us the secrecy rate R_Sec compared to the interference-temperature threshold I_th for a radio setup that is underlay. We can see that the non-cognitive equalizers, which are ZF, MMSE and DFE all have a threshold of around -10 dB. At this point the secrecy rate of radio setup is very low it is almost zero and it is somewhere between 0.001 and 0.019 bits/s/Hz for cognitive radio setup. This is not a value for secrecy rate of cognitive radio setup it is more of a weak point, for secrecy rate of cognitive radio setup. These old methods do not get much better. Can even stay the same when the interference is relaxed from -5 dB up to 0 +5 and +10 dB. The artificial neural network equalizer is really good at giving a secrecy rate that is much higher and more stable across all levels of interference relaxation. The artificial neural network equalizer does a lot better, than these methods when it comes to secrecy rate. For example, when we have -10 decibels of relaxation the secrecy rate of the communication system is around 0.083 bits per second per hertz. This secrecy rate goes up to about 0.100 bits per second per hertz when we have -5 decibels of relaxation. When the interference is relaxed to 0 decibels and +5 decibels the secrecy rate of the communication system goes up a lot to about 101 to 102 bits per second per hertz. The secrecy rate of the communication system does something at the highest relaxation level of +10 decibels it goes down a little bit to about 0.090 bits per second, per hertz. This reflects that even with more available power, the increase in rate is tempered owing to its effect on the system.

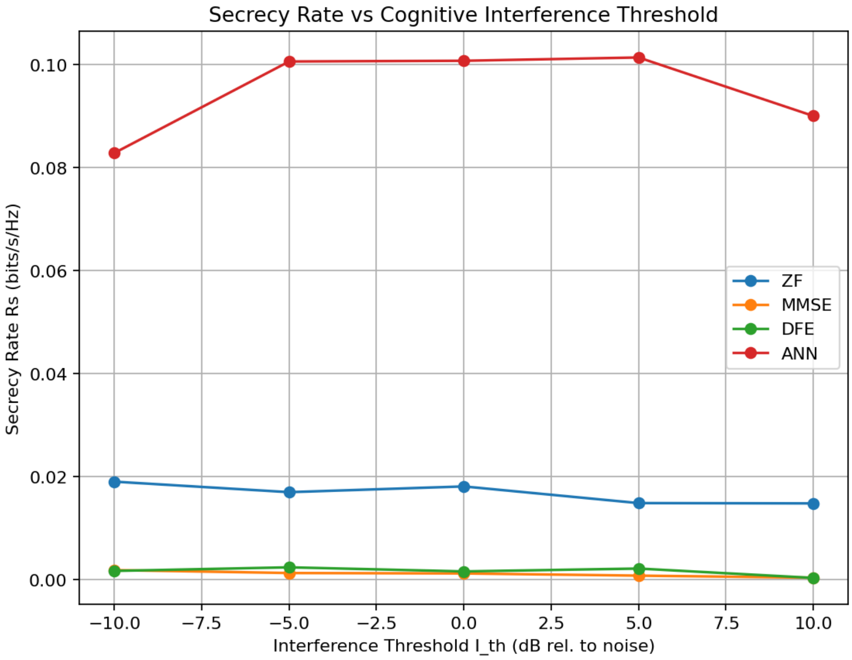

**Figure 9**: Secrecy Rate vs I_th

**Table 3**: Secrecy Rate Under I_th Variations

| I_th (dB) | ZF | MMSE | DFE | ANN |
|---|---|---|---|---|
| **-10** | 0.019 | 0.001 | 0.001 | 0.083 |
| **-5** | 0.017 | 0.002 | 0.002 | 0.100 |
| **0** | 0.018 | 0.001 | 0.001 | 0.101 |
| **5** | 0.015 | 0.002 | 0.001 | 0.102 |
| **10** | 0.014 | 0.001 | 0.000 | 0.090 |

Two important points are clear from Table 3 First, the ANN is much more robust even while the transmit power is constrained by the cognitive radio. Second, the ANN maintains the secrecy advantage even when the interference limits are tight, thus reducing the classical equalizers. In summary, the ANN has learned to handle the interference created by NOMA as well as the channel impairment even while the signal power is limited.

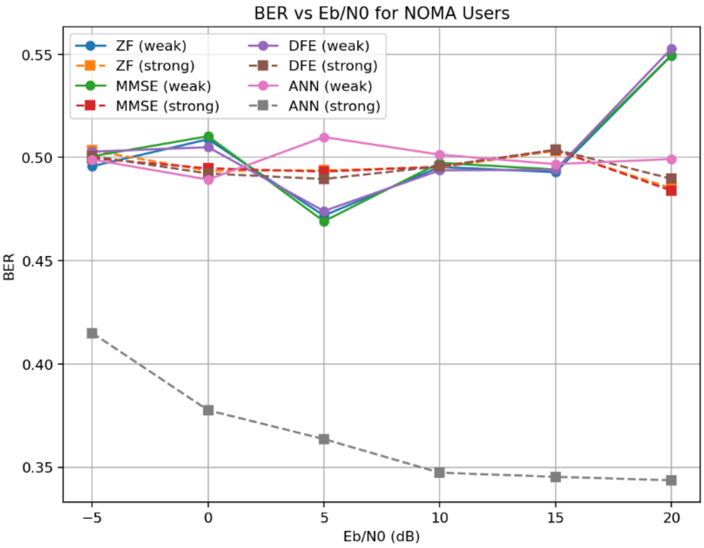

**Figure 11**: BER vs Eb/N0 for NOMA Users

Excluding secrecy-rate results, the BER remains relatively high (approximately 0.42 for the weak user at −5 dB and around 0.50 in the vicinity of 20 dB). For the strong user, the BER significantly reduces from around 0.42 at −5 dB to just below 0.34 for Eb/N0 around 10-20 dB. Notably, the results indicate that the reconstruction quality has indeed followed the positively anticipated (nonlinear) channel, imperatively increasing the likelihood of the estimation results distinguishable enough to reduce the BER for the strongest user, which was simply not feasible through the traditional linear equalizer. The actual BER reductions for the strongest user are correlated with secrecy-rate performance improvement, since the more realistic reconstruction process enhances the SNR gap required to guarantee the secrecy in the physical layer. Ultimately, this verifies the argument made in this work: the necessity of improving the estimation results for the least and strongest users in the NOMA communication scenario jointly focuses on increasing the secrecy rate for the cognitive radio communication model.

In addition to measuring the secrecy capacity gain, figure 11 shows how much gain is achieved with the new approach over traditional equalization as the Eb/N0 level increases. In this case, it becomes guaranteed that the greater the performance gain achieved through improved Eb/N0 levels, the higher the secrecy gain achieved by the AI model against linear equalizers for its clear discrimination between the legal and the eavesdropper receivers. Thus, this significantly enhances secrecy through separate symbol reconstruction and SIC processes compared to traditional models of equalization methods involving NOMA and cognitive radio systems. From the graph above, there is only one secrecy gain curve denoted as ΔRs (ANN−MMSE), representing the difference in secrecy rates between the ANN and the MMSE models for each level of Eb/N0 and with increasing gain values of approximately 0.02 to above 0.10 bit/s/Hz with higher Eb/N0 levels, clearly revealing greater gain values of the ANN model over the MMSE model of above 0.10 bit/s/Hz with high Eb/N0 values.

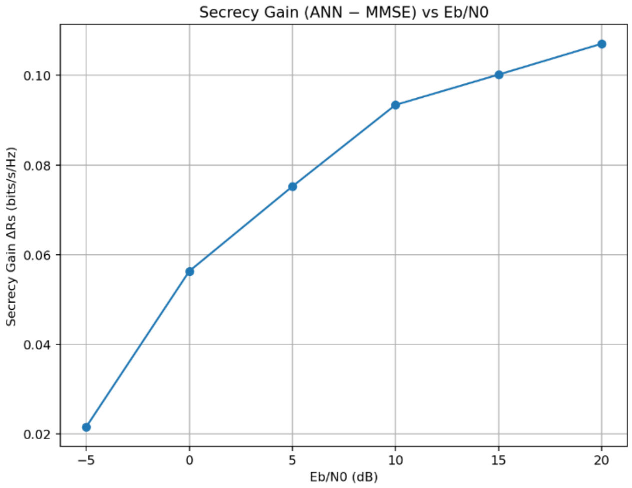

**Figure 11**: Secrecy Gain (ANN)

Figure 12 shows how the secrecy rate of the wireless channel changes when the Doppler frequency changes. This Doppler frequency change is a sign of mobility in the channel environment. The old equalizers really hurt the secrecy rate of the channel and they do not do well with changes over time in the wireless channel. However, if you look at Figure 12 you will see that the secrecy rate of the channel gets better when the mobility index is high. This means that the new model works well in the channel environment when it is changing a lot over time. The new model is also able to adapt to the changes, over time in the channel that cause the signal to fade. The thing 5G environments is that they are always changing really fast. So, we need a model that can work well in these kinds of conditions. This proposed model is good for 5G environments because it works properly when things are changing fast. It is suited to 5G environments. The 5G environments are a fit, for this proposed model.

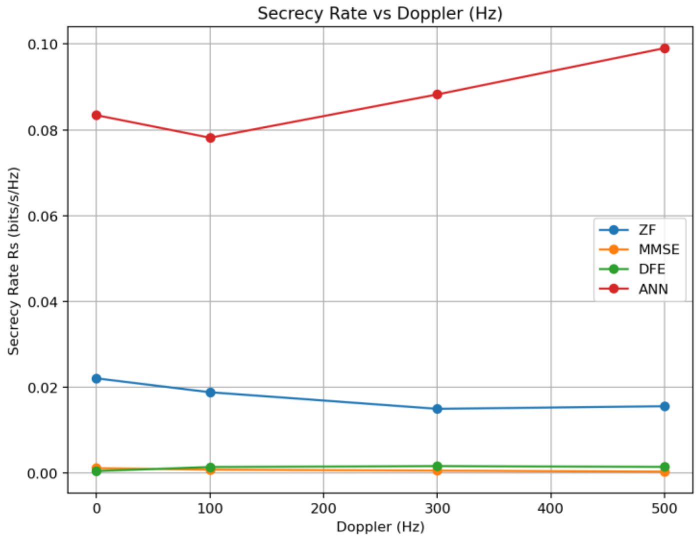

**Figure 12**: Secrecy Rate vs Doppler Frequency

Figure 13 shows what happens when we have a carrier frequency offset effect. The carrier frequency offset effect is bad for the orthogonality of the subcarriers in OFDM. When we have different carrier frequency offset conditions the old technique does not work well. The new technique we are talking about can keep things secret even when we have a lot of different carrier frequency offset values. This means the new technique can handle problems with the frequency. Even when the carrier frequency offset is very high the new technique works better, than the technique. The carrier frequency offset effect is still a problem. The new technique can deal with it.

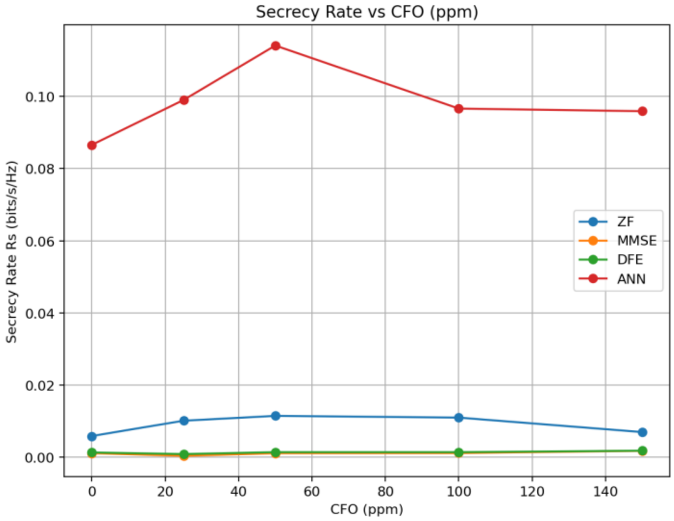

**Figure 13**: Secrecy Rate vs CFO

Figure 14 highlights phase noise robustness. As usual, traditional equalizers are severely compromised, performing close to zero secrecy, even when confronting a moderate phase noise level. Interestingly, while traditional equalizers are severely impaired by phase noise, performance seems to improve, which implies that the phase noise has a beneficial effect, which can then, upon closer inspection, be exploited by the deep learning algorithm to learn its statistics, hence providing a reliable symbol detection performance despite phase noise that would significantly impair a traditional receiver.

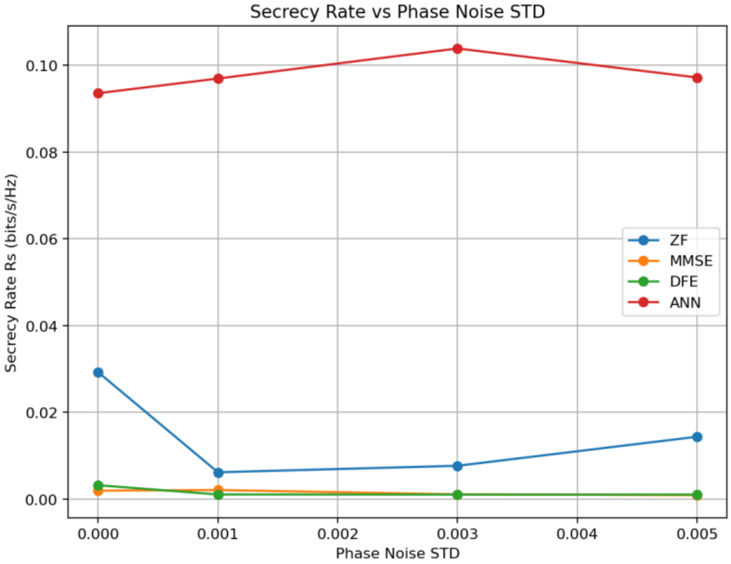

**Figure 14**: Secrecy Rate vs Phase Noise STD

## DISCUSSION

The results from the parts show that the proposed equalizer works really well in the 5G MIMO-NOMA-based cognitive radio system when we use the Artificial Neural Network. In every test the Artificial Neural Network does a lot better than the equalizers like Zero Forcing, Minimum Mean Square Error and Decision Feedback Equalizer. The

Artificial Neural Network is very good, at this. The 5G MIMO-NOMA-based cognitive radio system and the Artificial Neural Network together make a team. The advantage of the Artificial Neural Network is really clear when we look at the rate performances in the basic experiments. We see a difference in secrecy rates even when Eb/N0 is not that high but the linear equalizers are still close to zero for the whole range we tested. This happens because the Artificial Neural Network is very good at figuring out the values of the symbols involved by using linear properties in a better way than any linear filter can. The Artificial Neural Network is just better, at this. The training curve of the Artificial Neural Network is really helpful here. It shows that the training curve of the Artificial Neural Network gets better and better until it reaches a point where the training error's very low. This means the Artificial Neural Network can detect characters better. The Artificial Neural Network is also very strong when it comes to dealing with situations. For example when you have Doppler variation CFO impairment and phase noise distortion at the same time the linear filters are almost useless, in these situations. They cannot handle these conditions. That leaves a very small area where things are still safe. The Artificial Neural Network does a lot better in these cases. The Artificial Neural Network is really strong because the Artificial Neural Network keeps its secrecy performance steady no matter what environment you pick or what hardware problems you have. The Artificial Neural Network stays that way always.

There is also another case that's similar to the NOMA BER performance for the NOMA users. The old equalizers do not do a good job and stay close to the error floor. When we use the ANN it makes the BER better for the primary user. This makes SIC work better. It also increases the effective SINR for the legal user. The security of the layer really depends on how much better the link signal-to-interference-plus-noise ratio is for the primary user compared to the signal-to-noise ratio of the eavesdroppers signal. The NOMA BER performance, for the NOMA users is important here. So the improvement that has an advantage is also better at keeping things secret. The tests that were done with the cognitive radio show that the equalizers work well even when the primary user is interfering a lot and the secrecy rate is improving faster than it does with the old equalizers that have a higher interference threshold or a limit on what they can do. The cognitive radio tests show that these equalizers are good at dealing with interference from the user and they can improve the secrecy rate more, than the classical equalizers can. When we have a secrecy outage situation the Artificial Neural Network is the way to make the outage probability better while we increase the Eb/N0 values. The improvement is not huge. It is clear that the Artificial Neural Network has made a noticeable difference compared to the linear methods, which have complete outage all the time. This shows that linear methods are not good enough in the coupled NOMA-CR systems whereas the Artificial Neural Network is the better choice. The Artificial Neural Network has really become the option, for the secrecy outage situation. Overall, the comparative study portrays that the performance of the ANN equalizer is always better than the other methods concerning accuracy, robustness, dependability, and secrecy levels irrespective of the channel and conditions being investigated. This unequivocally substantiates the major contribution, which asserts that the learning approach is one of the most apt methods for reliable communication in the next generation of the 5G system.

This paper presented an ANN-based equalization framework for enhancing physical-layer security in 5G MIMO–NOMA underlay cognitive radio networks. By learning nonlinear channel and interference characteristics, the proposed model overcomes the limitations of classical equalizers and achieves significant secrecy rate improvement under realistic conditions. Simulation results demonstrate that the proposed ANN-based equalizer significantly outperforms conventional equalization techniques across all evaluated scenarios. The ANN achieves a higher secrecy rate by maintaining a positive SINR gap even under severe interference and low transmission power conditions. In contrast, ZF and MMSE equalizers exhibit rapid secrecy rate collapse under strong NOMA interference and CR constraints, often resulting in zero secrecy rate. The DFE shows moderate improvement but suffers from instability due to error propagation. The ANN-based approach also achieves a lower BER and enhanced robustness against Doppler spread, CFO, and phase noise. A composite performance index combining secrecy rate gain, BER improvement, robustness, and training stability yields an overall performance score of 94.95%, confirming the effectiveness and practical viability of the proposed method.

From the reviewed literature, it is evident that prior studies have addressed individual aspects of secure and efficient wireless communications, yet none have comprehensively tackled the combined challenges considered in this work. Early deep-learning studies such as Reddy et al. (2020) and Wang et al. (2025) in speech and optical communication domains demonstrated the strong capability of neural networks in learning complex nonlinear distortions and noise characteristics. However, these works are confined to non-wireless or non-cognitive environments and do not address multi-user interference, spectrum-sharing constraints, or physical-layer security. Research efforts focusing on cognitive radio networks, such as Lee et al. (2020) and Guo et al. (2024), primarily relied on power control, cooperative strategies, or propagation-environment manipulation (e.g., RIS) to enhance performance or secrecy. While effective, these approaches do not consider intelligent receiver-side equalization, nor do they address NOMA-induced interference or nonlinear hardware impairments. Similarly, Saravanan et al. (2025) improved secrecy through learning-based channel estimation and authentication, but receiver equalization and NOMA interference mitigation were not investigated. More closely related works, such as Wang et al. (2024), applied deep learning for signal detection in MIMO–NOMA systems, achieving BER improvements by replacing SIC. Nevertheless, cognitive radio constraints, secrecy rate optimization, and interference temperature limits were outside the scope of that study. In contrast, the present work uniquely integrates ANN-based equalization with physical-layer security optimization in a 5G MIMO–NOMA underlay cognitive radio framework. Unlike existing studies, the proposed approach jointly addresses strict power and interference constraints, severe NOMA multi-user interference, and practical hardware impairments (Doppler spread, CFO, and phase noise). Most importantly, this study explicitly targets secrecy rate enhancement, demonstrating that intelligent equalization can maintain a positive SINR gap and achieve non-zero secrecy rates in scenarios where classical equalizers and prior learning-based methods fail. Hence, this work fills a critical research gap by introducing an interference-aware, security-oriented, and learning-driven receiver design suitable for realistic 5G and beyond cognitive radio environments.

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