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ENHANCING THE PERFORMANCE OF WIRELESS NETWORKS EMPLOYING CSI AND AUTOMATED HANDOVER

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Abstract

As the technology paradigm shifts towards pervasive and connected networks, the automated handover among multiple access techniques becomes mandatory as varying channel conditions especially for mobile and connected devices results in fluctuating Quality of Service (QoS) for the network. In such cases, fading and interference effects result in sudden fading dips in the power level which accounts for significant variability in the error rates received at the receiving end of the network. Such a waxing and weaning power envelope at the receiving end also depends on the type of multiple access technique used, which makes it critically important to choose a technique which would result in satisfactory QoS as well as bandwidth efficiency for the overall network. Orthogonal Frequency Division Multiplexing (OFDM) and Non-Orthogonal Multiple Access (NOMA) happen to be the most well suited multiple access techniques or pervasive wireless networks such as IoT and edge computing networks. While OFDM is widely used in both long and short ranged networks such as Wifi, WLANS, WANs as well as LTE and VOLTE based network architectures, limited bandwidth in any network puts a fundamental limit on the users or user equipment (UE) data which can be accommodated for OFDM (which separates UE data in orthogonal frequency domain). The has led to exploring NOMA as an alternative, which separates UE data in power domain. As any one multiple access technique doesn't render satisfactory QoS under all channel conditions, hence, it is essential to employ a handover mechanism which can analyze channel parameters and switch from NOMA to OFDM when the performance of NOMA is estimated to be poor and again switch back from OFDM to NOMA when the estimating of QoS for NOMA is satisfactory. In this paper, a deep learning model is proposed to initiate automated handover among OFDM and NOMA based on channel metrics. The results show improved QoS metrics compared to benchmark models in the domain.

Keywords: Wireless Networks, Handover, Deep Learning, Channel State Information (CSI), Channel Metrics, Quality of Service (QoS).

1. Introduction

Wireless network have swiftly moved to the software defied networking (SDN) framework with the ease of interoperability and control over multiple layers of the OSI model. Typically, the SDN framework has the following distinctive advantages [1]:

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1. Mobility management.
2. Dynamic channel configuration.
3. Rapid client re-association.

One of the most important challenges to be addressed in the SDN framework applied to IoT, Edge Computing, Fog Networks and other pervasive networks is minimizing bit error rates and frame error rates constrained to the limited bandwidth of the network [2]. The issue is even more pressing with more UE data being generated through by a multitude of devices in a network, which is typically the case in the recent scenario. While, traditional wireless networks, which rely on static architectures and hardware-based control mechanisms, often struggle to meet these evolving requirements [3]. This is where Software Defined Networks (SDNs) emerge as a transformative solution, offering programmability, automation, and centralized control to enhance network performance and adaptability [4].
Conventional wireless networks are typically hardware-centric, with the control plane and data plane tightly coupled [5]. This rigid structure makes it difficult to reconfigure, scale, or optimize the network dynamically. Network operators face challenges in managing traffic congestion, mobility, and quality of service (QoS) as user demands and traffic patterns change frequently. Furthermore, the lack of centralized control limits visibility across the network, making troubleshooting, policy enforcement, and security management cumbersome. These constraints have created a pressing need for a more agile and intelligent networking approach. Software Defined Networking introduces a paradigm shift by decoupling the control plane from the data plane [6]. This separation enables centralized management of network resources through a software-based controller that can dynamically program and optimize the network. In wireless environments, SDN facilitates efficient resource allocation, seamless mobility management, and adaptive traffic routing. It also supports multi-tenant and multi-operator scenarios, which are essential for 5G networks and smart city applications. By allowing programmable network behavior, SDN empowers network administrators to quickly respond to real-time changes and optimize performance [7].

As 6G, Wi-Fi 7, and next-generation IoT applications continue to evolve, SDN plays a crucial role in supporting their complex requirements, one of the most critical of which happens to be automated handover among multiple access techniques [8]. The process of handover among multiple access techniques needs to be designed meticulously keeping in mind the SNR-BER characteristics being similar ensuring co-existence among the techniques [9]. The most effective approach in this direction is channel sensing or channel state information (CSI) based handover or handoff, wherein critical channel metrics are analyzed to initiate handover to preserve satisfactory QoS [10].

2. Channel Sensing

Wireless networks exhibit variability in the channel response based on several factors such as transmission frequency, topography, terrain, fading factors and movement of UEs [11]. This needs a continuous sensing mechanism which senses the channel periodically. Channel sensing plays a vital role in ensuring optimal spectrum utilization by identifying available or underutilized frequency bands [12]. When integrated with Software Defined Networks (SDNs), channel sensing becomes even more powerful, enabling intelligent and dynamic management of wireless resources through centralized control and programmability [13].

Channel sensing refers to the process of detecting the availability and condition of wireless communication channels before data transmission. It helps determine whether a channel is free or occupied, thereby reducing interference and improving communication reliability [14]. Traditional wireless systems rely on static channel allocation schemes, which often lead to inefficient spectrum use. In contrast, dynamic spectrum access—empowered by channel sensing—allows devices to opportunistically utilize vacant channels. This mechanism is crucial for cognitive radio networks and forms the foundation for efficient spectrum sharing in modern wireless systems [15].

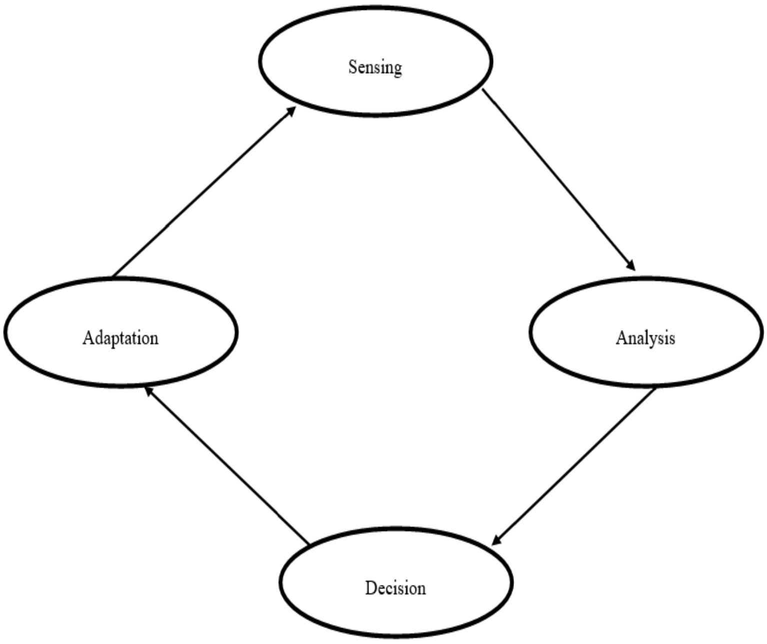

Figure 1. Process of channel sensing.

Figure 1 depicts the process of channel sensing which is done iteratively to estimate the most recent version of the channel state information (CSI). Channel sensing is essential for enabling adaptive and data-driven decision-making, especially handover [16]. Since SDNs separate the control plane from the data plane, the SDN controller can leverage channel sensing information to dynamically allocate channels, balance network loads, and mitigate interference. This allows for better spectrum efficiency and improved Quality of Service (QoS) [17]. Moreover, as wireless environments are inherently unpredictable due to mobility and varying interference levels, continuous channel sensing helps the SDN controller maintain real-time awareness of network conditions, ensuring stable and optimized operation. The channel sensing process has four major steps [18]:

1. Sensing
2. Analysis
3. Decision
4. Adaptation

The adaptability in SDN is rendered through the four steps carried out in continuum. The resulting CSI can be utilized both for handover and security aware channel assignment, against potential security attacks. The major challenge in this case though is the additional overhead created in the process of iterative sensing. Considering the sampled impulse response (IR) of the channel to be [19]:

$$\boldsymbol{h(t) = \sum_{i=1}^{n} h_n} \qquad \textbf{(1)}$$

Here,
h(t) represents IR of the channel (assuming LTI nature)
h(n) represents IR to single tone frequencies [20].

Using the Fourier Transform to convert from time domain to frequency domain:

$$\boldsymbol{H(f) = \int_{-\infty}^{\infty} h(t) e^{-j\omega t} dt} \qquad \textbf{(2)}$$

Here,
H(f) denotes response in frequency domain
ω denotes angular frequency
The iteratively sensing CSI of the channel is thus obtained as [21]:

$$\boldsymbol{H(f, nTs) = \sum_{i=1}^{n} H(f, t - nT_s)} \qquad \textbf{(3)}$$

Here,
Ts denotes channel sensing
n denotes number of samples
f denotes frequency metric

Typically, in case adversarial attacks are employed over the network bandwidth $\boldsymbol{B}$**,** the mean adversarial power over the bandwidth is computed as [22]

$$\boldsymbol{P_A = \frac{1}{N} \sum_{i=1}^{N} B_i S_i} \qquad \textbf{(4)}$$

Here,
P_A denotes mean adverarial power.
N denotes number of sub-bands
B denotes sub-bands of bandwidth
S denotes allocation per subband

The sub-band adversarial power can fluctaute over the entirerity of the bandwidth and the inequality for the mean power typially holds true as [23]:

$$\boldsymbol{P_{A-mean} \ll P_{A-S}} \qquad \textbf{(5)}$$

Here,
P_{A-mean} denotes adversarial mean.
P_{A-S} denotes instantaeous adversarial power.

Accurate CSI allows to identification and allocation of network baddwith only where attack ativity level is negligile or low.

3. Proposed Methodology

3.1 Proposed architecture

The proposed architecture of the work considers the fact that critical channel metrics are available to train a deep learning model. The critical channel metrics considered in this work are depicted in figure 2.

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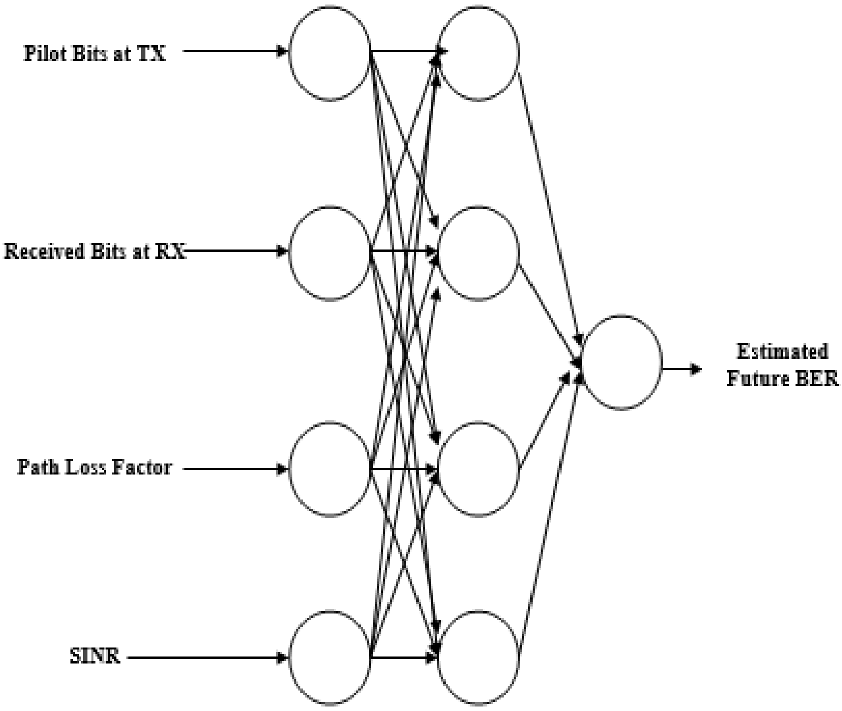

Figure 2. Channel Metrics to train model

Figure 2 depicts the structure of the model which is to be trained with channel parameters. For SDNs, ne of the critical challenges in modern wireless systems is accurately estimating and predicting the Quality of Service (QoS) in highly dynamic environments [24]. Traditional analytical and rule-based models often fail to capture the complex, nonlinear relationships between diverse channel conditions and resulting network performance. With the advent of deep learning, it has become possible to model such intricate dependencies and make data-driven QoS estimations [25]. By training deep learning models using channel parameters such as pilot bits, received bits, Signal-to-Interference-plus-Noise Ratio (SINR), and path loss factor, it becomes feasible to obtain accurate and adaptive QoS predictions in real time [26].

Channel parameters such as pilot bits, received bits, SINR, and path loss factor serve as vital indicators of wireless link quality. Pilot bits provide reference signals that help measure channel state information (CSI), while received bits indicate data integrity and transmission success [27]. SINR reflects the effective signal quality amid interference and noise, and the path loss factor quantifies the attenuation experienced over distance and environmental conditions [28] When these parameters are used as input features for a deep learning model, they collectively provide a comprehensive view of the network's physical and link-layer conditions, enabling precise estimation of QoS metrics such as throughput, delay, and packet loss rate [29].

In designing a deep learning model for QoS estimation, the selection of architecture is crucial [30]. Models such as Deep Neural Networks (DNNs) well-suited for processing time-series and spatial channel data [31]. The training dataset is typically generated from real-world measurements or simulated wireless environments, capturing diverse scenarios of mobility, interference, and traffic load [32]. During training, the model learns to map input parameters—

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pilot bits, received bits, SINR, and path loss-to-output QoS indicators. As the channel condition varies over time, it is necessary to obtain the time varying CSI for the channel shown next [33]:

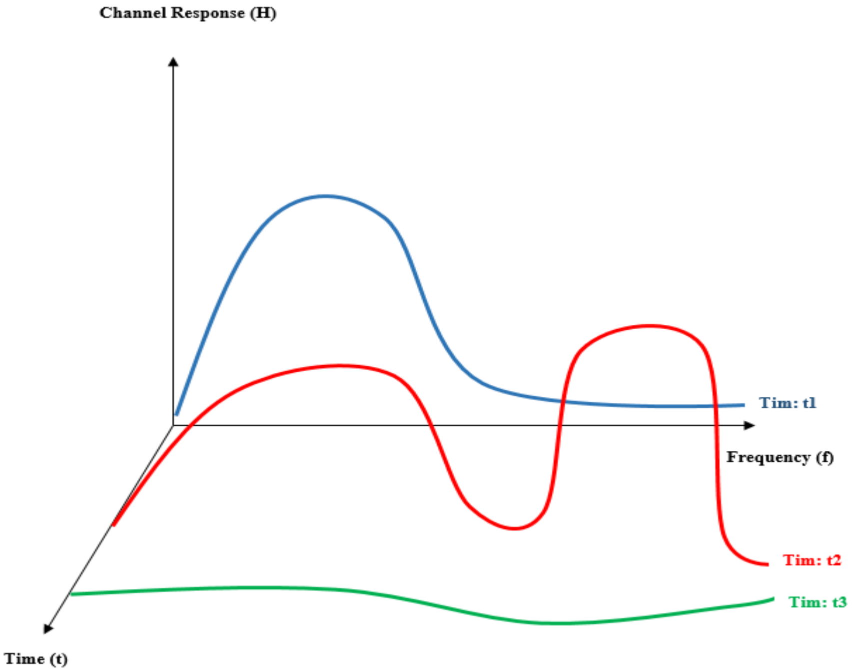

Figure 3. Time varying CSl

Figure 3 depicts the time varying CSl which is a function of both time and frequency metrics. It is important to note that most wireless channel do not follow ideal magnitude and frequency characteristics given by [34]

$$\boldsymbol{H(\omega) = K \forall \omega} \tag{6}$$

$$\boldsymbol{P(\omega) = -l(\omega) \forall \omega} \tag{7}$$

Here,
$H(\omega)$ denotes ideal magnitude response of channel.
$P(\omega)$ denotes ideal phase response of channel.
ω denotes angular frequency:

$$\boldsymbol{\omega = 2\pi f} \tag{8}$$

K is a constant
$-l(\omega)$ denotes a linear function

As the magnitude response deviates from remaining constant and the phase response deviates from linearity, it is necessary to choose the sampling time $\boldsymbol{T_S}$ such that it capture the piece wise constant and linear nature of the channel accurately. The fading in case of any wireless network depends on the amount of attenuation undergone given by [35]:

$$\alpha = \sqrt{\frac{\omega\mu}{2}\left(\sqrt{1+(\frac{\sigma}{\omega\epsilon})^2}\right) - 1} \tag{9}$$

Similarly, the phase constant is given by [35]:

$$\beta = \omega\sqrt{\frac{\epsilon\mu}{2}\left(\sqrt{1+(\frac{\sigma}{\omega\epsilon})^2}\right) + 1} \tag{10}$$

The challenge is to develop and algorithm which can be leveraged for both initiating handover as well as secure channel assignment based on the CSI.

3.2 Algorithm:

The algorithm for the handover between Access Technique 1 (NOMA) and Access Technique 2 (OFDM) is presented next:

```
Start
{
Step.1: Generate random binary data as pilot bits as:

$X_{pilot} = rand(N, X_{pilot})$

Step.2: Design a random channel response as:

$h_{Channel} = rand(n, B) : \sigma_{near} \gg \sigma_{far}$

Step.3: Generate frequency response of channel as:

$H(f)_{Channel} = fft\ (rand(n, B) : \sigma_{near} \gg \sigma_{far}$

Step.4: Generate white noise and create additive white Gaussian noise (AWGN) channel conditions as:
$N_{Channel} = \frac{N}{2}\ \forall f$

Step.5: On passing data stream through channel using both multiple access techniques, the channel output can be obtained as:

$Y(f) = H(f).X(f) + N_{Channel}$

Step.6: (for t=1:$T_s$)
        {
```

```
        Employ channel sensing as:
        $H(f, t - nT_s)$
        }

Step.7: Split samples into training and testing in the ratio of 70:30

Step.8: Design deep neural network model fed with input neurons as channel parameters
and output neuron being the QoS metric.

Step.9: Define the value for validations checks $(val)$ for $k - fold$ validation.

Step.10: Define the cost function J for least squares optimization,

$J = \underbrace{min}_{over\ i} \quad \frac{1}{n}\sum_{i=1}^{n}(p_i - \widehat{a}_i)^2$

Step.11: Check for following conditions:

if $(i \leq maxitr \ \& \ val \neq k - fold)$
{
Update weights as:
$w_{k+1} = w_k - \alpha[H]^{-1}\frac{\partial e}{\partial w}$
}
else
{
Truncate training.
Compute MSE and BER
}

Step.12: Estimate BER for both OFDM and NOMA

Step. 13: Check for co-existence based on SINR-BER characteristics and decide feasibility
of handover as:

if ( OFDM and NOMA exhibit similar SINR-BER characteristics),

        Initialize handover as:
        if $(BER_{NOMA} < BER_{OFDM})$
        {
        Continue with NOMA
        }
        else
        {
```

```
        Switch to OFDM
        }

else (handover not feasible)

Step. 14: To identify secure bandwidth, check condition:
                                $\mathcal{R}_i \leq \mathcal{R}_T \; \forall \; n \epsilon B$
}
Stop.
```

Here,
fft *denotes Fast Fourier Transform.*
rand denotes random.
f denotes frequency.
t denotes the time metric.
X_{pilot} *denotes bits per frame.*
N denotes bits per frame.
B denotes bandwidth.
n denotes number of sub-carries in bandwidth.
σ_{near} and σ_{far} *denote near and far user fading factor.*
k and $k+1$ *are the iterations.*
w_k & w_{k+1} *are the weights.*
e is the iteration error.
p_i and $\hat{a}_i$ *denote predicted and actual values.*
J denotes the cost function.
$\mathcal{R}_i$ and $\mathcal{R}_T$ *denote instantaneous channel response and threshold channel response corresponding to secure condition.*

4. Result analysis

The system has been simulated on MATLAB on a PC with Intel i7 processor and 16 GB of RAM. The toolboxes utilized are:

1. Statistical
2. Deep learning
3. Wireless networks.

The experiment is run for 10 million random bits with frame size of 32. For the sake of simplicity, $1.6 * 10^3$ binary bits have been presented for illustration. A higher power level corresponds to logic 1 and lower power levels corresponds to logic level 0. The channel considered in the simulation is the AWGN channel, which has the property of identical noise PSD over the entire bandwidth of usage, which implies that all the sections of the bandwidth are affected by noise effects. The results obtained through the simulation are presented subsequently:

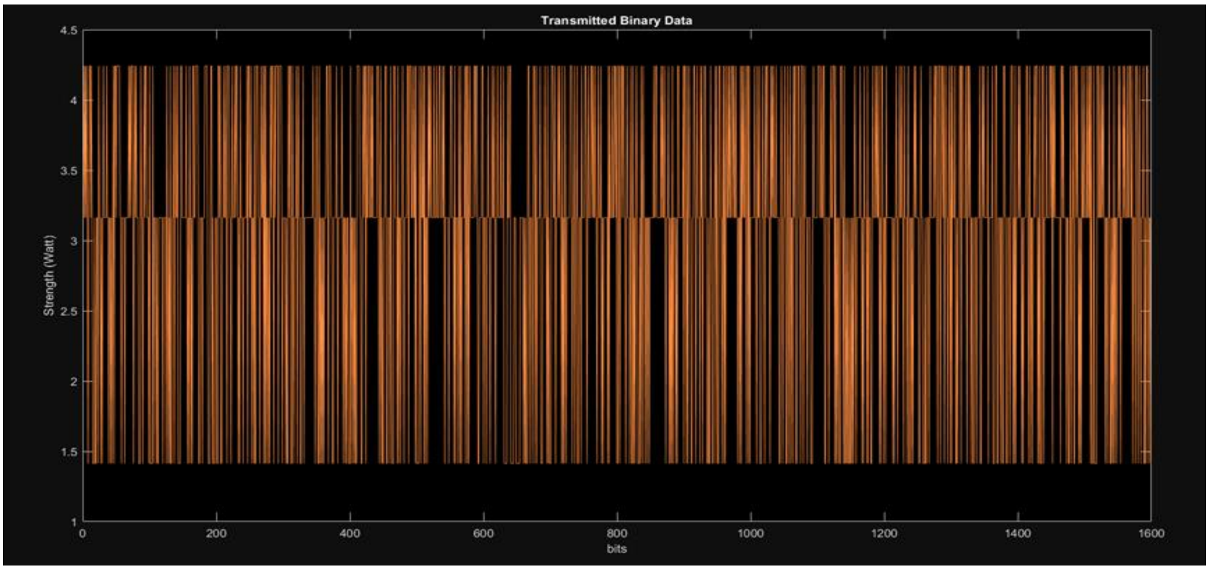

Figure.4 Binary data generated

Figure 4 depicts the random binary pattern generated which corresponds to the random data which would have been generated through the UEs or IoTDs in any practical wireless network, and subsequently transmitted.

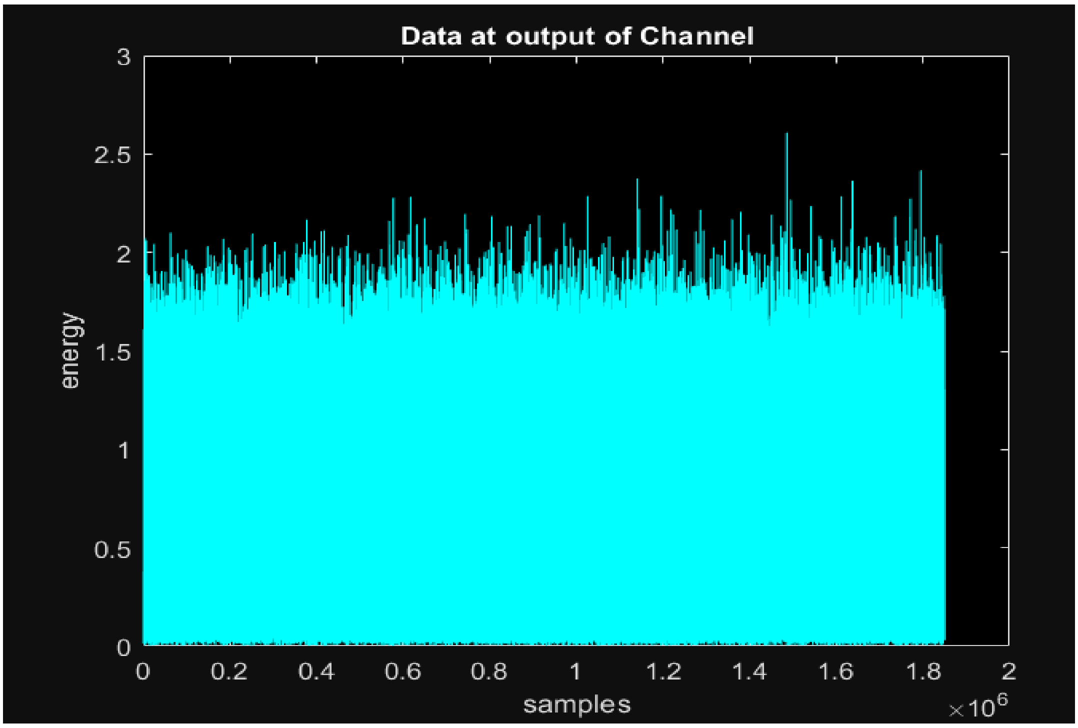

Figure.5 Data at output of channel after noise addition

Figure 5 depicts the output of the channel after noise addition. It can be observed that distortion occurs in the channel both due to noise addition and non-ideas characteristics of the channel.

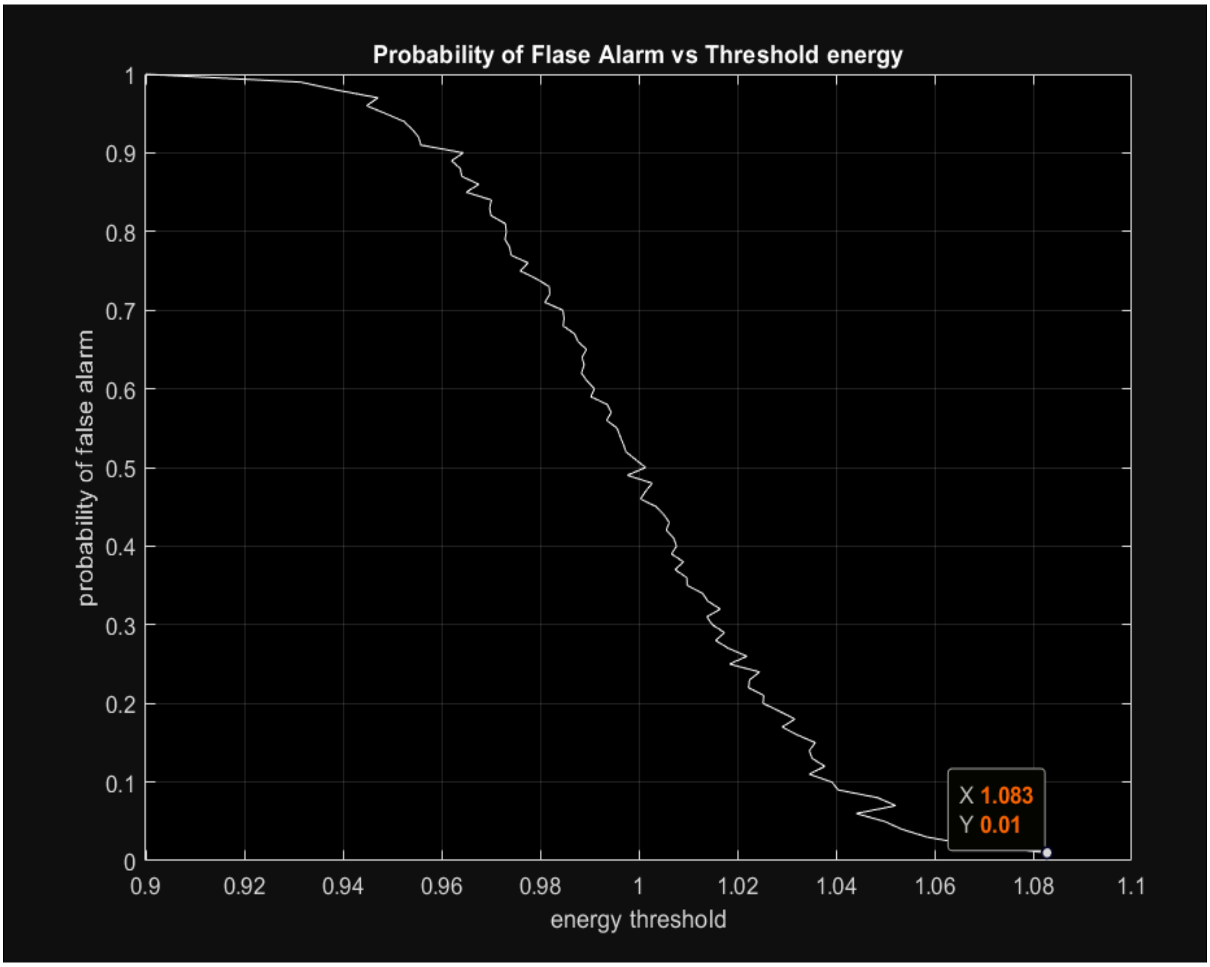

Figure.6 False alarm probability

Figure 6 depicts the probability of the false alarm of identifying potential adversarial attacks based on the threshold of identifying attacks as per the following relation:

$$\boldsymbol{\mathcal{R}_i \leq \mathcal{R}_T \,\forall\, n \epsilon B}$$

In this case, the values of **original** $\boldsymbol{\mathcal{R}_i}$ is considered **0.3** while that of **instantaneous** $\boldsymbol{\mathcal{R}_i}$ at the receiving end would depend on the continuous bit stream arriving at the receiving end of the network. The value of $\boldsymbol{\mathcal{R}_T}$ is considered to be **0.5** based on the fact that some amount of signal strength would be increased at the receiving end due to the addition of noise in the channel, which is why the effective threshold is chosen as 0.5. Sub-carriers with response magnitude $\boldsymbol{\mathcal{R}_i > 0.5}$ are likely to have a high potential of adversarial attack. The false alarm probability drops to 0.01 i.e. 1% as the energy threshold increases indicating the fact that the signal strength overrides the noise and adversarial power in the bandwidth.

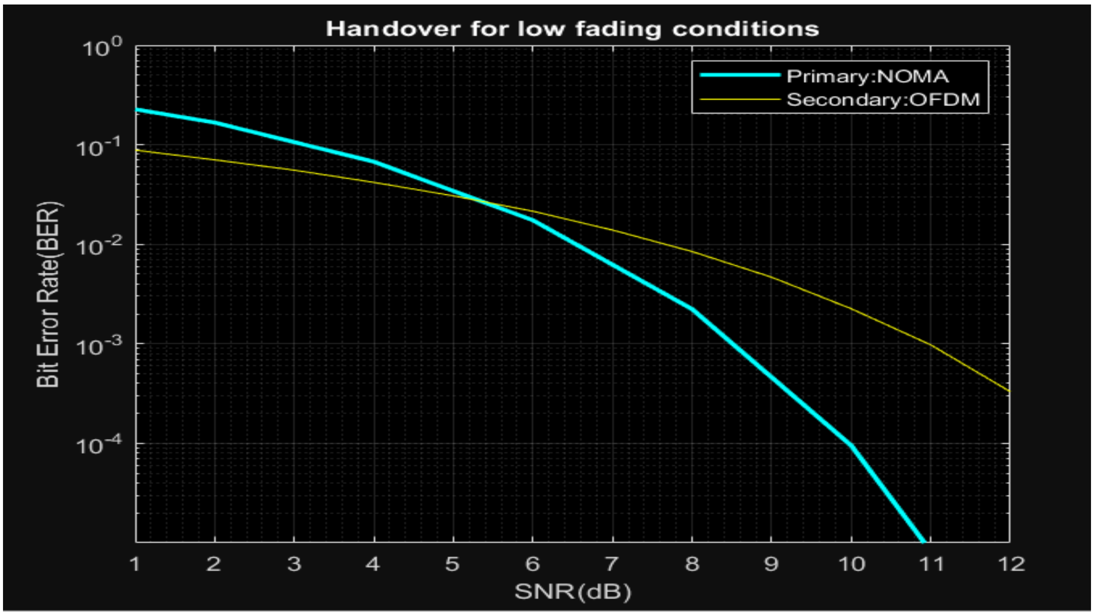

Figure.7 Handover under low fading

Figure 7 depicts handover under low fading i.e. when the path loss factor is low with relatively higher SNR at the receiving end.

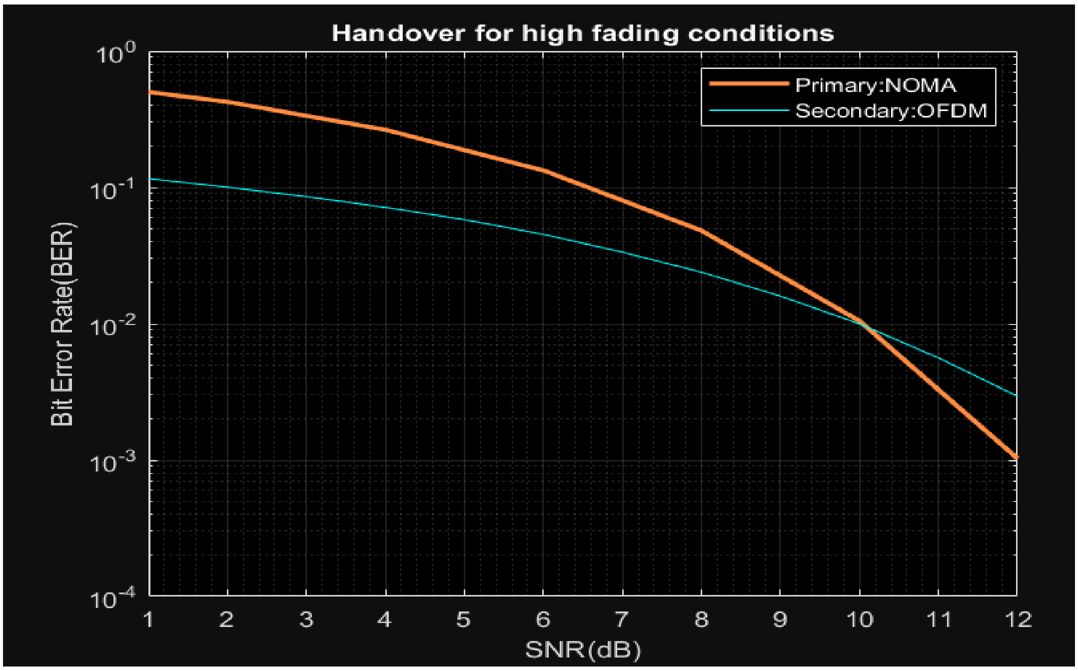

Figure.8 Handover under high fading

Figure 8 depicts handover under high fading i.e. when the path loss factor is high with relatively lower SNR at the receiving end.

Important Observations:

It can be observed that at lower SNR values, OFDM's BER is relatively lower than NOMA while at higher SNR values, NOMA's BER is lower than that of OFDM. Additionally, at the intersection point, handover should be initiated. OFDM avoids intra-cell interference by assigning orthogonal subcarriers to different users, ensuring interference-free communication. At low SNRs, where noise is dominant, this inherent lack of interference helps maintain signal fidelity and reliability. NOMA (Non-Orthogonal Multiple Access): NOMA relies heavily on Successive Interference Cancellation (SIC) at the receiver to separate the superimposed signals of multiple users sharing the same frequency/time resource. The effectiveness of SIC is highly dependent on a sufficient power difference (channel gain difference) between users and good channel estimation. At low SNRs, the noise floor is high, making it difficult for the receiver to accurately perform SIC. Thus, the results show that show that NOMA's performance can struggle with balancing fairness for users with poor SNR can be worse than OFDM at low SNR values. Thus, a meticulously designed handover mechanism is needed to accurately initiate handover under varying fading conditions. A summary of results is presented in Table 1.

Table 1 Summary of Results:

S.No	**Parameter**	**Value**
1	Simulation Platform	MTLAB
2	Bits in simulation	10 million
3	$Primary$	NOMA
4	$Secondary$	OFDM
5	ML Model	Deep Neural Networks
6	Model Architecture and Algorithm	Back Propagation
7	Training Parameters	4
8	Cost Function	MSE
9	Handover SNR (Low Fading)	6dB
10	Handover SNR (High Fading)	10dB
11	Probability of False alarm	1% (0.01)
12	BER of [26]	10^{-2}
13	BER of [27]	10^{-3}
14	**BER (Proposed Work)**	$\mathbf{10^{-4}-10^{-5}}$

It can be observed that the proposed work successfully simulates the binary data transmission under distinct multiple access techniques, being NOMA (primary) and OFDM (Secondary). Moreover, the approach is able to initiate handover at both low and high SNR conditions at the receiving end. Further, the model is able to attain very low probability false alarm in case of identifying potential adversarial activity in order to implement secure bandwidth assignment.

5. Conclusion

With increasing number of users and devices in pervasive wireless network, the search for optimal multiple access techniques stands as a fundamental requirement. While conventional access techniques have relied on frequency domain separation among UE data streams, limited bandwidth availability has resulted in search for newer multiple access techniques such as NOMA which separates UE data in the power domain. NOMA has a distinctive advantage of higher spectral efficiency yet rendering low latency. However, due to the dependence of the technique on power level separation among data streams, fluctuating power levels arising out of random channel behavior, especially for mobile devices tends to increase the error rates for NOMA. This results in degrading BER and QoS, typically at lower SNR levels. This necessitates an automated handover mechanism under varying SNR conditions at the receiving end. The proposed work implements a deep learning approach in which channel parameters are used to train a deep neural network to estimate the error rate as the target of the deep learning model. Additionally, a security aware channel assignment is designed based on the channel response under effects of noise and adversarial attacks. The probability of false alarm obtained in this case is 0.01. The handover SNR in low and high fading cases in 6dB and 10dB respectively, with the respective BER being 10^{-4} *and* 10^{-5}, clearly outperforming existing work in the domain.

Future directions of research may focus on computing the accuracy of the handover deep learning model and analyzing the scatter plots for multiple channel response conditions.

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