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A Machine Learning Based Approach for MIMO Channel Estimation in Wireless Networks

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***Abstract:** Current wireless networks are facing the challenges of increased number of users, the amount of bandwidth availability to be used by the users and the need for ever increasing data rates. The major concern regarding all the problems is the high capacity expectation from wireless channels. However, wireless channels are often random in nature with frequency selective nature at the basest. The limitation in the bandwidth support by any channel makes the data rate support to be limited. In this paper, a machine learning based CSI enabled MIMO system has been designed and has been employed to commonly existing diverse channel conditions. To increase the spectral efficiency and simultaneously reduce the BER of the system, the Maximum Ratio Combining (MRC) approach has been used along with MMSE and ZFE equalization techniques. The proposed system has been simulated on Matlab. The performance of the system has been evaluated in terms of the Bit Error Rate and Spectral Efficiency of the system. The proposed machine learning based MIMO system has been shown to improve upon the performance of existing work in the domain of research.*
***Keywords:** Wireless Networks, Machine Learning, Channel Estimation, Multiple Input Multiple Output (MIMO), channel state information (CSI), Deep Learning, Bit Error Rate (BER), Spectral Efficiency.*

I. INTRODUCTION

MIMO systems are the need of the hour due to the capability to increase channel capacity even at limited bandwidth systems. Practical channels seldom follow the ideal characteristics of gain and phase response. However, the degradation of the BER performance of MIMO systems is a serious concern to achieve satisfactory QoS [1]. Off late machine learning and artificial intelligence based techniques are being explored for MIMO decoding due to the fact that such systems are capable of pattern recognition for large datasets in limited time [2].

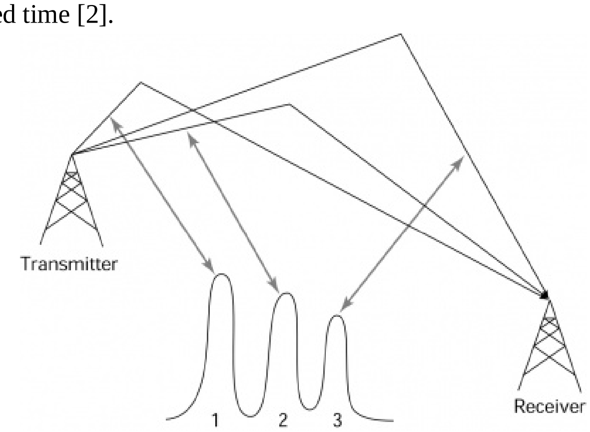

Fig.1 Multipath Propagation

Multi-path propagation results in the non-ideal characteristics of channel response which happen to be a constant gain response with respect to frequency and an negative linear phase response with respect to frequency. The conditions can be mathematically represented as [3]:

$$H(\omega) = K \; \forall \; \omega \tag{1}$$

$$P(\omega) = -l(\omega) \; \forall \; \omega \tag{2}$$

Here,

$H(\omega)$ represents the magnitude response of the channel.
$P(\omega)$ represents the phase response of the channel.
ω represents the angular frequency given by:

$$\omega = 2\pi f \tag{3}$$

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

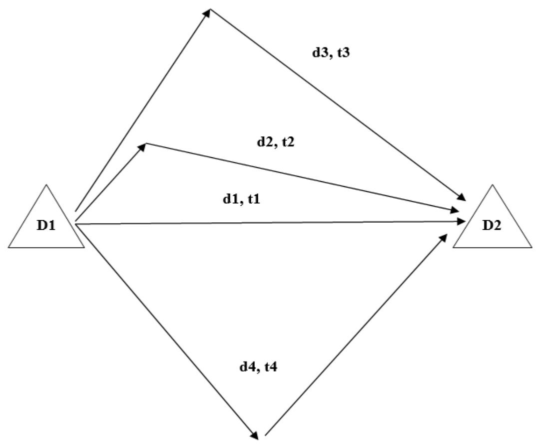

Fig.2 Effect of Multipath Propagation

Multipath propagation results in a non-ideal impulse response of the system. The aforesaid factors makes it mandatory to design equalizers which can reverse the negative effects of the non-ideal channel [4].
Another problem arising out of multi-path propagation mechanisms is the distributed impulse response of system given by [5]:

$$h(\omega) = h_1 g_1 + \cdots \ldots \ldots \ldots . h_n g_n \tag{4}$$

or

$$h(\omega) = \sum_{i=1}^{n} h_i g_i \tag{5}$$

Here,
$h(\omega)$ is the composite impulse response
h_i is the individual impulse response of a particular path
g_i denotes the individual path gain of a path.
Thus a composite signal comprising of multiple copies of the data results in the overlap of signals causing interference often leading to a Poisson based distribution. The probability distribution function of such a distribution (which governs the receiver power) is given by [6]:

$$P(X, n) = Prob\,(X = n) = \frac{Z^n e^{-Z}}{n!} \tag{6}$$

Here,
X denotes the random variable
n denotes the occurrence number
e denotes the Euler's constant.
With respect to the present scenario, Z denotes the received power and 'n' denotes the number of multi path components in the communication media [7]. As the available radio spectrum is limited, higher data rates can be achieved only by designing more efficient signalling techniques. Recent research in information theory has shown that large gains in capacity of communication over wireless channels are feasible in multiple input multiple output (MIMO) systems as well as significantly enhances the system performance compared to conventional systems in fading multipath channel environment [8].

The MIMO channel is constructed with multiple element array antennas at both ends of the wireless link. All these MIMO techniques are based on proper handling of (Alamouti scheme and maximum ratio combining method) signals transmitted and received by an array of antennas. Simulation results show very high performance in terms of bit error rate, even for low signal-to-noise ratio Multiple Input Multiple Output (MIMO) systems are once such avenue [9]. MIMO systems increase the channel capacity manifold compared to Single Input Single Output (SISO) systems thereby enabling higher data rate transmission for the same bandwidth. MIMO technology has attracted attention in wireless communications, because it offers significant increases in data throughput and link range without additional bandwidth or transmit power. It is achieved by higher spectral efficiency (more bits per second per hertz of bandwidth) and link reliability or diversity (reduced fading) [10] Because of these properties, MIMO is an important part of modern wireless communication standards such as IEEE 802.11n(Wifi), 4G, 3GPP Long Term Evolution, WiMAX and HSPA. The schematic for a typical MIMO system is depicted in figure 3.

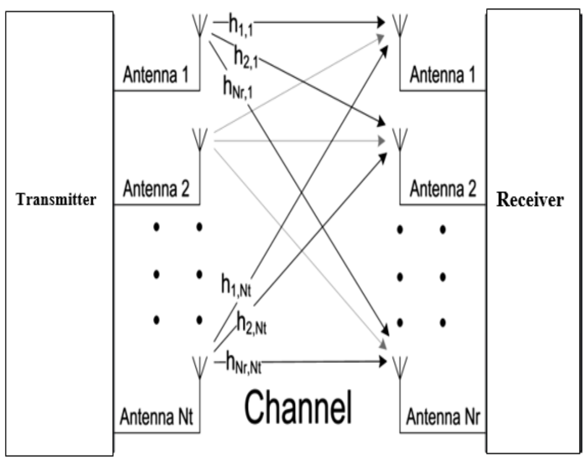

Fig.3. Conceptual model of a MIMO system

The MIMO based system has multiple transmitter and multiple receivers which create parallel data paths for transmission and reception which in tem allows enhanced data rates for the same limited bandwidth [11]. To implement this MIMO based transmission scheme practically, Space Time Block Coding (STBC) is often employed in which the data stream is arranged as a matrix with the number of columns equating to the number of MIMO transmitters and the number of rows equating to the number of time slots of transmission. The symbols of STBC transmission can be estimated as [12]:

$$H^{+} = (H^{H}H)^{-1}H^{H} \quad \textbf{(7)}$$

Here,
H^{+} represents the Moore-Penrose pseudo inverse since the channel matrix,
H is the channel matrix and it may not always be square for the STBC matrix. Typically, the channel capacity is enhanced as per the following relation:

$$C = f\{kBlpg_2\left[1 + \frac{h_{ij}^2 S}{N}\right]\} \quad \textbf{(8)}$$

Here,
C is the channel capacity
B is the channel bandwidth
S is the signal power
N is the noise power
k is a constant depending on system parameters
f is a function depending on system parameters
h is the MIMO channel matrix
i is the number of transmitters
j is the number of receivers

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Here,
x1, x2 … xn are the different sub-carriers for OFDM transmission
n is the total number of carriers
T is the period of the carriers
The system comprising of MIMO-OFDM suffers from frequency selective nature of channels and thereby encounters degraded BER performance in general [13].

II. MACHINE LEARNING FOR MIMO SYSTEMS

As mentioned earlier, the data being transmitted and received is staggeringly large which makes it extremely challenging to accurately estimate the channel characteristics in time critical applications. Hence, neural networks are being used off late to accurately estimate channel characteristics. Neural networks can model the relationship between received signals and transmitted symbols in a MIMO system, learning this mapping through training on large datasets [14]. Deep learning architectures such as fully connected neural networks (FCNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) have been employed to decode MIMO signals. These models can approximate the ML decoding function with significantly reduced computational complexity during inference. Moreover, neural networks can adapt to varying channel conditions without requiring explicit channel state information (CSI) if trained appropriately [15].

A typical mathematical equivalent of a neuron is depicted in figure 4. It is a neuron with multiple inputs.

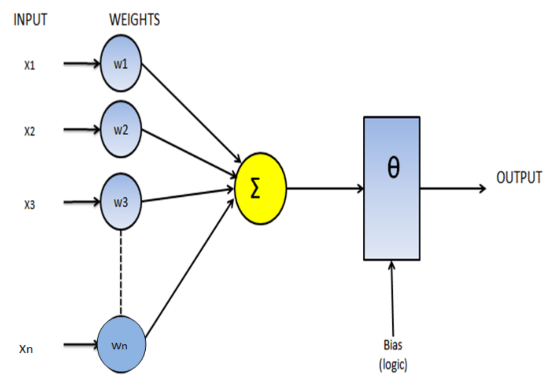

Fig.4 Mathematical Model of Neuron

In case the neurons are connected to each other to render a network, the neural network is depicted in figure 5.

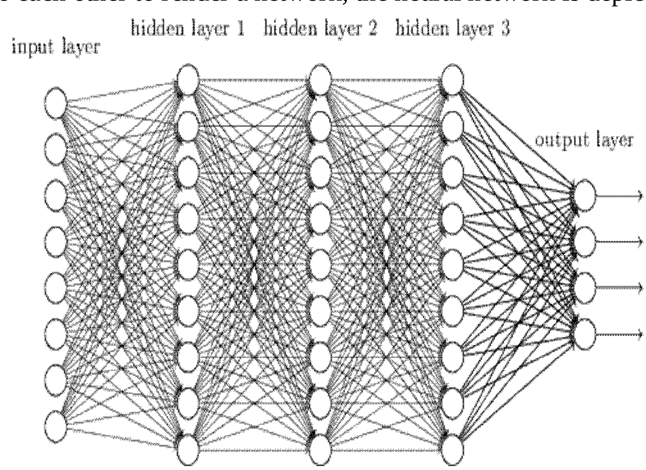

Fig.5 A typical Neural Network

The neural network is employed to estimate the channel characteristics in the following manner:
Step 1. Generate dummy data (binary stream) for training.
Step 2. Pass the data through the channel.

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Step 3. Provide the equalizer (Neural Nework Based) with the data being sent originally and the stream after passing through channel.
Step 4. Design a trainig Rule.
Step 5. Use the channel state inforamtion to perform equalization.
Step 6. Compute the BER of the system.
A typical training rule can be given by:

$$w_{k+1} = w_k - \left[J_k J_k^T + \mu I\right]^{-1} J_k^T e_k \tag{9}$$

Here,
W are the weights
K is the iteration number
e is the error
J is the Jacobian

The BER-SNR relation is plotted for simulation as:

$$\left(\sum_{i=1}^{n} \frac{Bit_{RX} \neq Bit_{TX})}{\forall all\ bits\ 'n'\ as\ a\ function\ of\ SNR}\right. \tag{10}$$

Typically, wireless channels depicts frequency selective nature i.e. they behave differently for different frequencies. Moreover, the frequency selectivity is not fixed by also exhibits temporal variation [8].

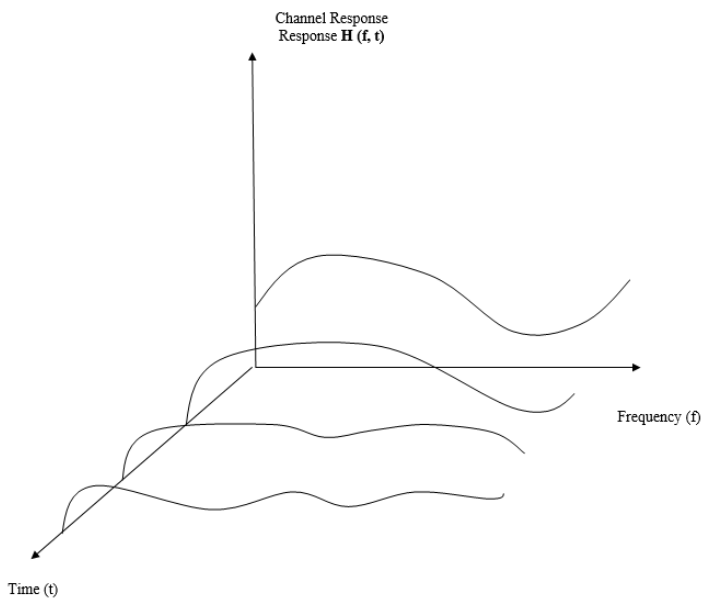

Fig. 6. Frequency Response of typical wireless channels

The composite impulse of the wireless channels corresponding to multi-path propagation effects can be given by [16]:

$$h(t) = \sum_{i=1}^{n} h_n \tag{11}$$

Here,
h(t) is the composite impulse response of the channel.
h(n) corresponds to each of the responses to single tone frequencies.
To convert the impulse response of the channel into the time domain, we compute the Fourier Transform given by [17]:

$$H(f) = \int_{-\infty}^{\infty} h(t) e^{-j\omega t} dt \tag{12}$$

Here,

H(f) is the channel response in frequency domain
ω is the angular frequency
The sampled version of the channel response is given by:

$$H(f, nTs) = \sum_{i=1}^{n} H(f, t - nT_s) \tag{13}$$

Here,
Ts is the sampling time for channel sounding
n is the number of samples
f is the frequency metric

For OFDM transmission, often to reduce the effects of frequency selectivity of channels, the cyclic prefix (CP) is inserted and is given by [18]:

$$S_{CP} = S_n - S_{n-k} \tag{14}$$

Here,
S_{CP} is the samples in the cyclic prefix
S is the original signal
n are the total number of samples
(n-k) are the samples which are appended as the cyclic prefix

Noise effects in case of wireless channels are inevitable and it becomes even more prominent with different paths of the MIMO system seeing a slightly different channel condition [19]. Thus it becomes necessary to mitigate the effects of such a frequency selective channel [20]. It can be done by the design of an equalizer which tries to revert the effects of the channel. The design of the equalizer requires the information regarding the channel response h(f). Since any practical system can sense the channel in the discrete time domain, therefore the channel impulse response can be re-considered as h(n) [21]. Let the channel in the frequency domain be H(z). Then the output of the channel is:

$$y(n) = x(n) * h(n) \tag{15}$$

$$Y(z) = X(z).H(z) \tag{16}$$

Where, * stands for convolution
x(n) is the input to the channel
y(n) is the output of the channel
The aim at design of an equalizer is the design of a system with a transfer function

$$E(z) = \frac{1}{H(z)} \tag{17}$$

The equalizer is placed just before the receiver and its performance depends greatly upon the accuracy with which the channel is estimated in the first place [22].
While there are different equalization techniques which can be employed, equalization used in the proposed system is the deep learning assisted zero forcing equalization which owing to its relative simplicity of implementation can be incorporated with massive MIMO systems. The mathematical formulation for the block linear equalizer (BLE) with zero forcing (ZF) approach is mathematically is given by [23]:

$$\hat{d}_{c,ZF-BLE} = (A^H R_n^{-1} A)^{-1} A^H R_n^{-1} e \tag{18}$$

Or,

$$\hat{d}_{c,ZF-BLE} = d + (A^H R_n^{-1} A)^{-1} A^H R_n^{-1} n \tag{19}$$

Here,
$\tilde{d}_{c,ZF-BLE}$ represents the zero forcing term
d are the desired symbols
$(A^H R_n^{-1} A)^{-1} A^H R_n^{-1} n$ is the residual noise term
H is the MIMO channel response
R_n is the Choleski decomposition of a conventional matched filter at the receiver
$A^H R_n^{-1}$ is the response of a typical whitening matched filter.
The SNR per symbol at the output of the ZF-BLE is given by [24]:

$$\gamma_{ZF-BLE}(k,n) = \frac{E\{|d_n^k|^2\}}{(A^H R_n^{-1} A)_{i,i}^{-1}} \tag{20}$$

Here,
E is the expectation of average value of the random variable
n is the symbol number
k is the number of samples

Considering correctness at the output of the ZFE, the output is given by [17]:

$$\gamma_{ZF-BLE}(k,n) = E\{\left|d_n^k\right|^2\}|\Sigma|_{i,j}^2 \tag{21}$$

The Minimum Mean Square Error (MMSE) algorithm tries to minimize the mean square error as the objective function (G)
Here, the errors in channel estimation can be minimized by employing the following relation [25]:

$$G = minimize\ (\frac{1}{n}\sum_{i=1}^{n} e_i^2 \tag{22}$$

Here,
G denotes the objective function
e denotes current error sample value
n denotes the number of error samples
The zero forcing equalizer tries to force the mean square error (mse) of the channel estimation to zero. Mathematically, equalization is performed if [26]

$$x(k) = [0_M \quad I_M]\begin{bmatrix} u(k-1) \\ u(k) \end{bmatrix} + E\frac{W_M}{\sqrt{M}} Z_r r(k) \tag{23}$$

Here,
MxM is the matrix size
u is the received signal
x is the recovered or equalized signal
W are the weights of the equalizer
E is the expectation or average value

III. SIMULATION RESULTS

The system has been designed on Matlab. The neural network design and the subsequent BER evaluation is presented.

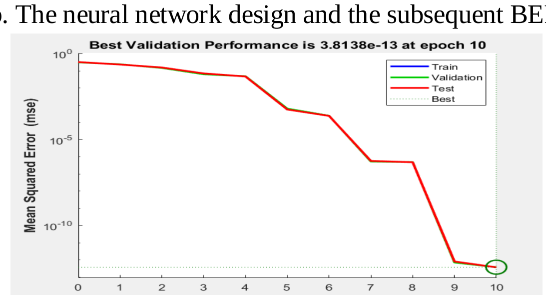

Fig. 7. Model Convergence

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The performance of the proposed system is evaluated in terms of the bit error rate (BER). This is also indicative of the actual channel capacity of the channel in terms of the error free data transmission.

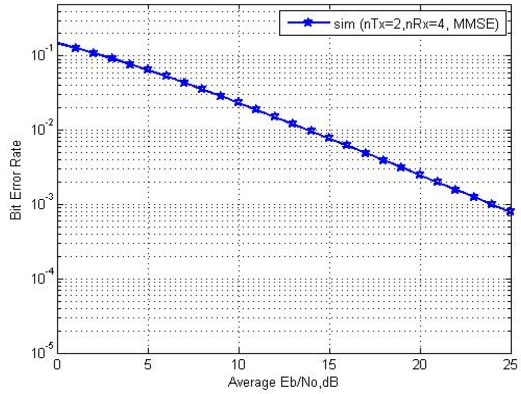

Fig. 8. BER Analysis for 2X4 MIMO with MMSE

Figure 8 depicts the MMSE based decoding for the 2 x 2 MIMO.

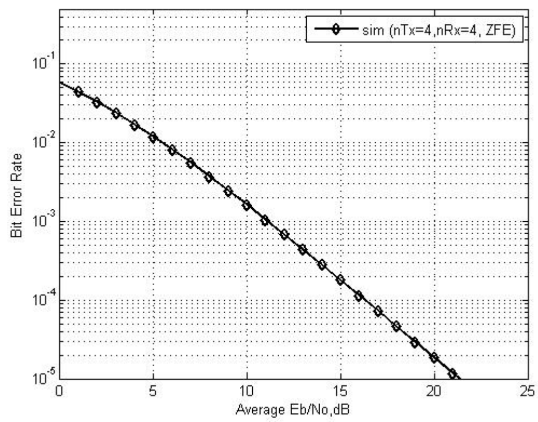

Fig.9. BER Analysis for 2X4 MIMO with ZFE

Figure 9 depicts the zfE based decoding for the 2 x 4 MIMO.

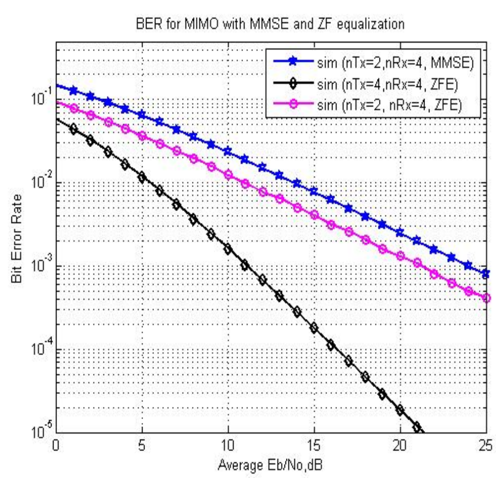

Fig. 10. BER Analysis for 2X4 and 4X4 MIMO with MMSE and ZFE

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Figure 10 depicts the combined BER analysis for MMSE and ZFE approaches.

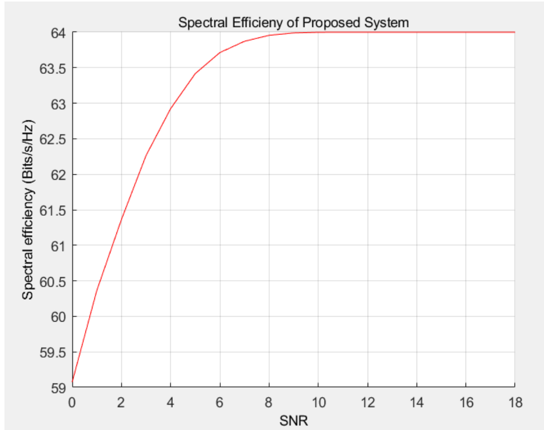

Fig. 11. Spectral Efficiency of Proposed System

Figure 11 depicts the systems spectral efficiency.

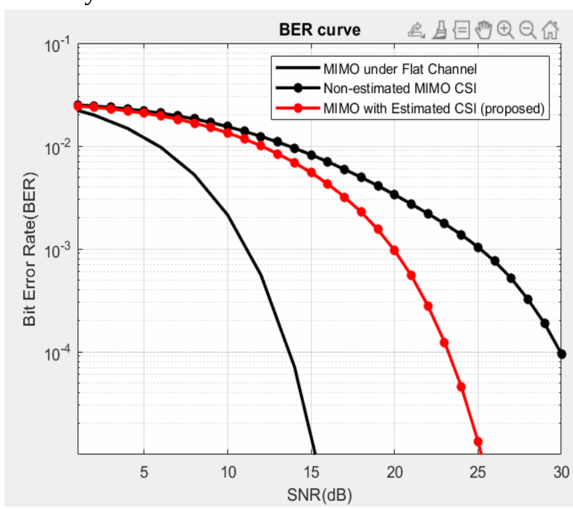

Fig. 12. Obtained BER

Figure 12 depicts the obtained BER of the system.
The summary of results is tabulated in Table I

TABLE I
Summary of Results

S.No.	Approach	BER Value
1	MMSE	10^{-3}
2	ZFE	10^{-5}
3	Tx=2, Rx=2	In between 10^{-3} and 10^{-4}
4	Tx=4, Rx=4	10^{-5}
5.	DNN Based MIMO Decoding	10^{-5} at 25dB
6.	CNN Model. [27]	10^{-3}

IV. CONCLUSION

It can be concluded from the previous discussions that MIMO systems can be considered to be key enablers in high data rate wireless networks. Neural network-based decoding offers an effective approach for enhancing the performance and efficiency of MIMO systems. By learning from data, these models can overcome many of the limitations of traditional decoding methods, particularly in complex and dynamic environments. As wireless communication continues to evolve toward higher capacity and lower latency, the integration of deep learning into MIMO decoding is likely to play a pivotal role in the development of next-generation communication systems. Due to multi path propagation and fading effects, it becomes necessary to employ channel estimation and MIMO decoding in conjugation with equalization. Two deep learning assisted techniques employing MMSE and ZFE techniques are proposed in this paper. It can also be observed that ZFE performs better than the MMSE approach for equalization for MIMO systems. Additionally, a comparative analysis with existing work in the domain clearly indicates the improved performance of the proposed work.

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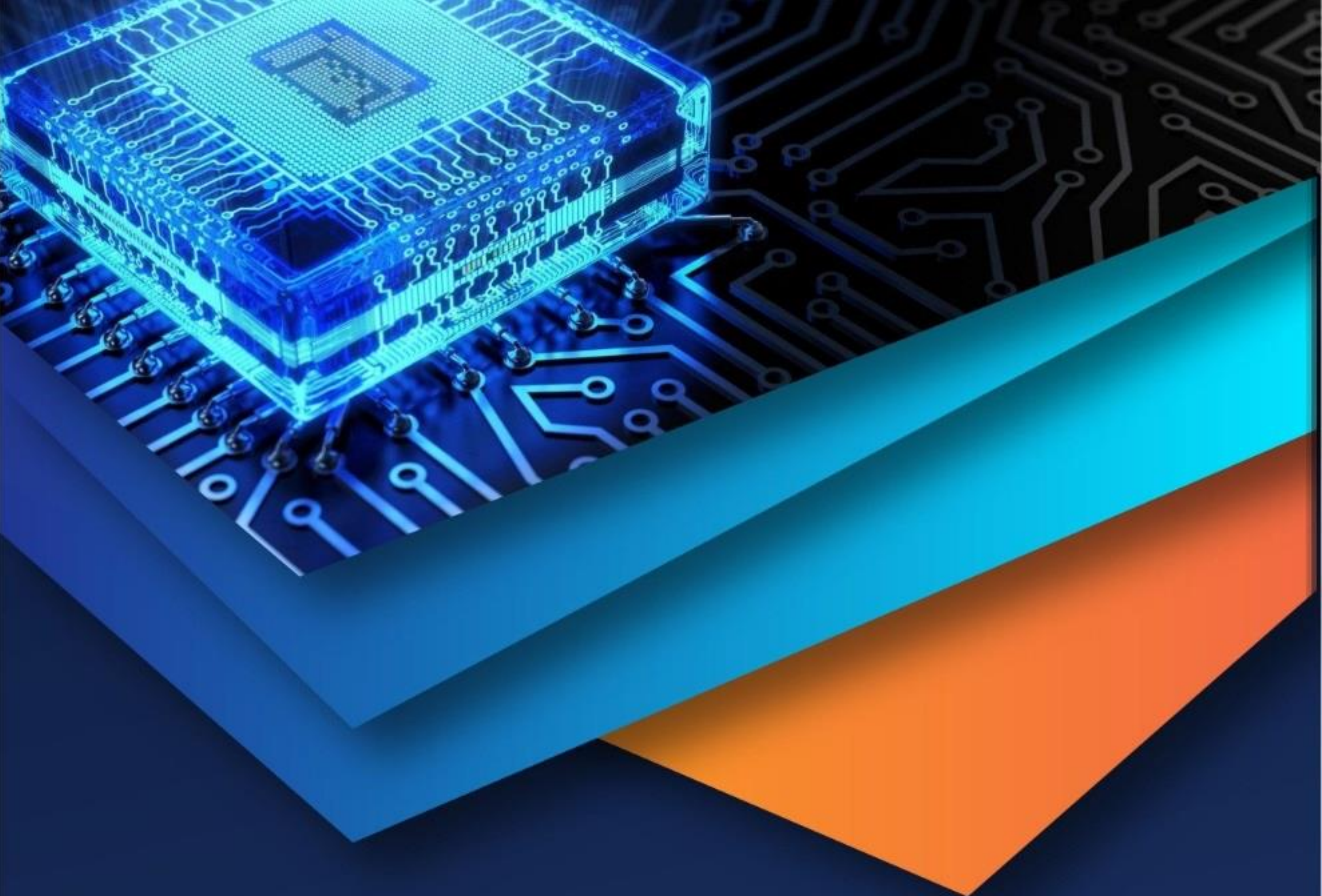

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