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MIMO OFDM SIGNAL DETECTION USING DEEP LEARNING

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ABSTRACT

In the communication system, signal detection at the receiver plays a key role in recovering back the original signal transmitted. OFDM is one of best technology for high data rate wireless transmission applications. The OFDM along with the array of antennas can be used to drastically increase the capacity of the system and the gain of the diversity which results in the MIMO OFDM configuration. We use the deep neural network algorithms to manage the wireless MIMO OFDM channels end to end. From our simulation results, the deep learning-based technique detect transmitted symbols with performance much better than any other traditional estimators. The findings using deep neural networks can provide good accuracy while maintaining the resilience against varying channels and noise variance by requiring much less complexity.

Index Terms *- Deep Learning, MIMO, Neural Networks, OFDM, Signal Detection*

1. INTRODUCTION

ORTHOGONAL frequency division multiplexing (OFDM) is a popular multi-carrier modulation technology for wireless broadband networks that splits a high data rate stream into a number of lesser data rate stream that has been widely utilized in wireless broadband systems. OFDM is the basic architecture of several important wireless communication technologies, including WiFi, LTE, and 5G. Multi Input Multi Output (MIMO) is a wireless communication method that uses multiple antennas at the transmitter and receiver. The strong combination of MIMO and OFDM can deliver an upgraded communication system with extraordinarily high spectrum efficiency and data throughput while eliminating the risk of inter symbol interference (ISI) and signal equalization. OFDM modulation offers an interface to manage the high data rate MIMO transmission by converting the high data rate channels into a large number of parallel low data rate channels.

In the literature [1]-[3], many methods are proposed to detect the signals at the receiver end in OFDM systems. These methods provide deep intuition on channel estimation and signal detection in OFDM systems where the deep neural network models are trained offline based on the simulation data that view OFDM and the wireless channels as black box and online deployment of that model may exactly align only with the channel models used in the training stage. These Deep Neural Network (DNN) can be used for estimating the channel reducing the effort of complex computations using algorithms like back propagation by processing with Fast Fourier Transform (FFT). It is also noted that, the cyclic prefix which are added to OFDM signal for mitigating ISI which in turn increases the bandwidth usage and decreases in energy per bit. As the Bit Error Rate (BER) increases with increase in number of multipath channels in both OFDM with CP and OFDM without CP as in the case of MIMO which needs to be reduced to provide accurate signal recovery at the receiver end.

In [4], MIMO detection is compared with various detectors and proposed a DNN architecture called DetNet for MIMO detection using deep learning. The suggested DetNet model has shown to be computationally cheap and has near-optimal accuracy. A comprehensive outline of the emerging research on deep learning models is given in [5]. In [6 A Parallel Detection Network (PDN) was developed, which comprises of many deep learning networks running in parallel but not connected. A model driven deep learning network is designed by adding some adjustable parameters to the existing decorators [7]. During training, a weight scaling framework based on monotonically non-increasing profile functions is dynamically prioritized by using a percentage of the layer weights [8]. [12] provides a deep learning approach which is competitive for broader range of MIMO channels. But, setting up deep learning would be quite difficult for specific channels which requires approximation of functions. These deep learning models show a significant improvement in the performance with a few limitations like computational complexity and training resources. Most of the time data is of limited size for learning, which could limit the capabilities of deep learning model. There could also be generalization error for the deep learning models as they are trained using simulation-based data.

Though a variety of methods are proposed to improve the performance of the signal estimation and recovery at the receiver end, still it is a challenging task to reduce the Bit Error Rate (BER) in high-end applications The findings of the Single Input Single Output experiment are described in this study (SISO) system using deep learning and then later moving onto MIMO systems with the combination of OFDM. A significant reduction in the BER could be observed even at low Signal to Noise Ratio’s (SNR) using deep learning methodologies.

2. TRADITIONAL MIMO OFDM SETUP

The modulated frequency domain signals are first turned into parallel data stream at the transmitter side of the communication system, which consists of numerous transmitters and receivers using OFDM modulation. A cyclic prefix is introduced after applying the Inverse Discrete Fast Fourier Transform (IFFT) to reduce ISI. It is sent in the channel through many transmitters after serial to parallel conversion and MIMO encoding. The signal can now travel in various directions before reaching the receiver. When several receive and transmit antennas are employed, the channel throughput may be increased linearly with each pair of antennas added to the system. After MIMO decoding, the typical OFDM demodulator at the receiver end removes the cyclic prefix from the received bit stream data and performs a Fast Fourier Transform. The receiver receives the recovered bits after serial to parallel conversion and mapping.

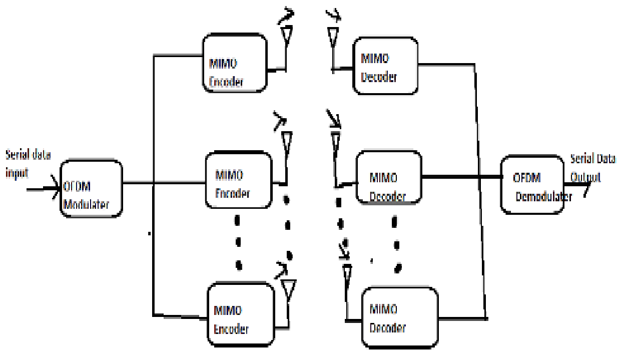

Fig. 1. General MIMO OFDM system

To increase the performance of the communication system, many existing approaches combine MIMO with OFDM. However, the main drawback of these methods is that MIMO require higher hardware complexity than simple SISO system and the more hardware usage increases the power requirements. Motivated by the performance of DetNet architecture in [4], we have utilized the idea of DetNet architecture for MIMO in combination with OFDM for efficient performance in the receiver unit and to combat the hardware complexity.

3. MATHEMATICAL ANALYSIS OF MIMO

For the standard linear MIMO model considered, the received vector at the receiver end is mathematically given by,

$$y = Hx + w \quad \text{.........(1)}$$

where, $y\epsilon\mathbb{R}^{N}$ denotes the received vector, $H\epsilon\mathbb{R}^{NXK}$ is the channel matrix, $x\epsilon\{\pm1\}$, where K denotes an unknown vector of independent and equal probability binary symbols, and $w\epsilon\mathbb{R}^{N}$ denotes a noise vector of independent, zero mean Gaussian variables of variance σ^2 . We do not presume the knowledge of the variance since, according to hypothesis testing theory, it is not essential for the effective detection. Indeed, knowledge of σ^2 is not needed for the best ML rule. Minimum Mean Square Error (MMSE) and other traditional decoders for signal bits detection at the receiver end, on the other hand, rely on this parameter and are hence less dependable.

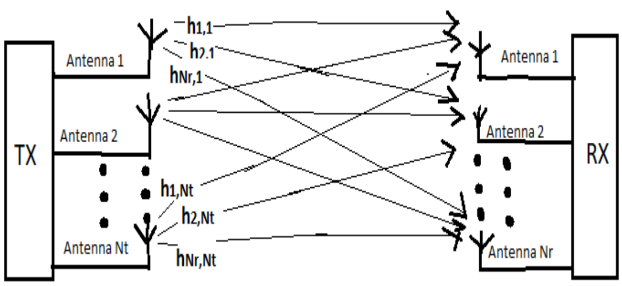

Fig. 2. NXN MIMO system

Equation shows the usual expression for the received vector at the receiver (1). At the receiver to recover the input, many popular techniques like Zero Forcing could be applied. We multiply the received vector with the inverse of the channel matrix to estimate the input at the receiver. The following is the result:

$\hat{x} = H^{-1}(y)$

$\hat{x} = H^{-1}(Hx + w)$

$\hat{x} = x + H^{-1}(w)$ ……….(2)

From equation (2), it can be seen that the estimate signal $\hat{x}$ could be same as original input x if the noise (w) is very less. And if the H is ill-conditioned, then H^{-1} matrix could have large elements which could amplify the noise. And when the channel is known at the transmitter it could be pre-coded with zero forcing detectors then, we get the following:

$\hat{x} = H(H^{-1}x) + w$

$\hat{x} = x + w$ …………….(3)

From equation (3), it can be observed that the ill-conditioned channel could be prevented to impact the estimated bits at the receiver end.

4. MODELLING THE SYSTEM

Modeling of the MIMO OFDM system with K subcarriers, N transmit, and M receive antennas, and signaling across a frequency selective fading channel is depicted below:

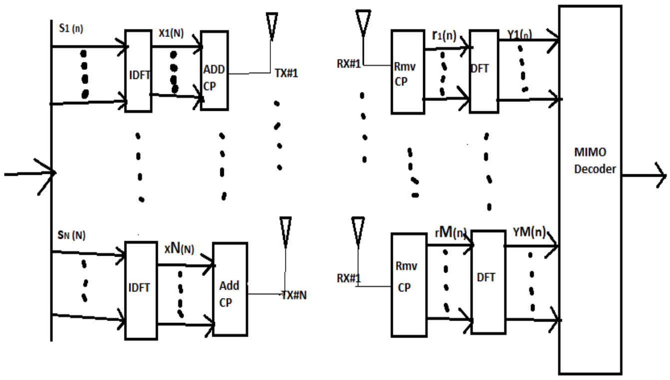

Fig 3. NXM MIMO OFDM system

Usage of multiple carriers allows easy multiuser resource sharing by allocating difference sub carriers to different signals. To eliminate multiuser inter symbol interference, the Cyclic Prefix (CP) must be included. The length of the CP represents the number of samples that are copied from the end of the modulated block to the beginning or vice-versa. The arrays of data carriers and pilot carriers are used to determine whether a subcarrier carries data or a pilot, and all of them are classified under OFDM carriers. The IDFT technique is used to convert the OFDM data to the time domain. The symbol is given a cyclic prefix. This procedure appends a copy of the OFDM time domain signal's final CP samples to the beginning or end. The signal is now delivered via the channel utilizing MIMO encoding methods. Following MIMO decoding at the receiver, the signal is converted back to the frequency domain using a DFT operation so that the received value of each subcarrier may be obtained.

5. ESTIMATING THE SIGNAL USING DEEP LEARNING

Deep Learning is the subfield of the artificial intelligence that uses multiple layers of abstraction to extract the deeper level of features from the data. Recent AI research for wireless communications has made significant progress in bringing deep learning techniques and other machine learning algorithms to the physical layer for diverse signal processing. The combined impacts of learning and the detection capabilities of the standard optimum detector are described, and an unique deep learning approach called DetNet is developed [4] which is now being connected with the OFDM system, based on ML projected gradient optimization. This method is important as it derives a learnable signal detection architecture for many number of channels on a unique training shot with good optimized performance and lower inference complication. A generative model for detecting the signal has been proposed with channel condition recovery network (CCRNet) in [13] which uses a group of SNR values for training.

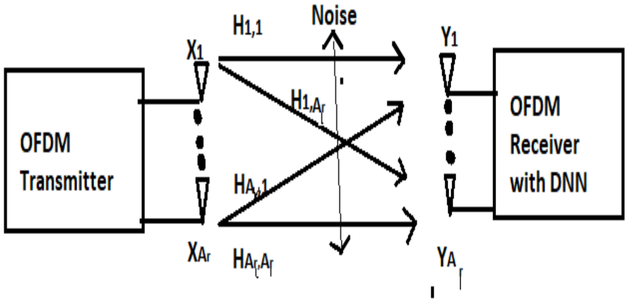

Fig. 4. Proposed System Model

The sequential model used to develop a deep neural network model is shown in the diagram below. It is the simplest model that allows for layer-by-layer addition of neurons. Each layer has weights that are identical to those of the one above it. In a dense layer, all nodes in the previous layer are linked to nodes in the current layer. Models using an activation function can take into account nonlinear interactions. ReLU, or Rectified Linear Unit Activation Function, is the activation function employed. From simulation results of [14], it is observed that the performance of the decoder improves on increasing the network layers but by those trainable parameters increases there by increasing the complexity of the algorithm.

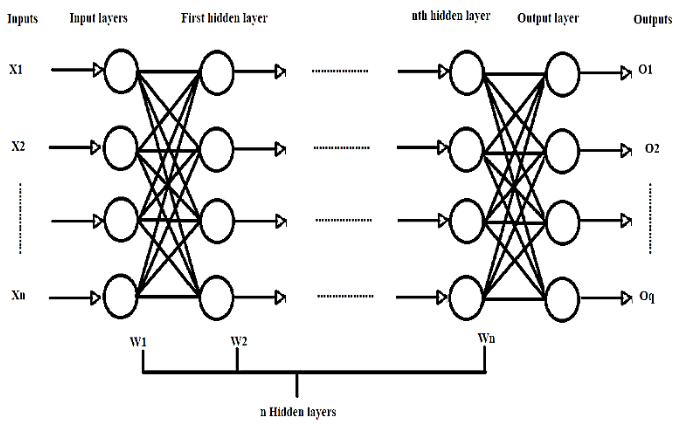

Fig. 5. Deep Neural Network

It employs the notion of deep unfolding, which allows one to develop a better MIMO detector by extracting information from an existing MIMO detection method. Deep learning detectors have the purpose of training the detection network off-line and then using it immediately in time-varying channel settings. The detector here used is:

$$H^T y = H^T H\, x + H^T w \;\ldots\ldots(4)$$

This suggests that H^T y and H^T H x in (4) should be two key elements in the architecture of the deep neural network model. The following equation is used to estimate the signal at the receiver:

$$\hat{x} = (H^T H)^{-1} H^T y \;\ldots\ldots(5)$$

The projected gradient descent solution for maximum likelihood optimization is used to build the layer in the design. This method would result in iterations of the following form:

$$\begin{aligned} \hat{\mathbf{x}}_{k+1} &= \Pi\left[\hat{\mathbf{x}}_k - \delta_k \left.\frac{\partial\|\mathbf{y}-\mathbf{H}\mathbf{x}\|^2}{\partial\mathbf{x}}\right|_{\mathbf{x}=\hat{\mathbf{x}}_k}\right] \\ &= \Pi\left[\hat{\mathbf{x}}_k - \delta_k\mathbf{H}^T\mathbf{y} + \delta_k\mathbf{H}^T\mathbf{H}\mathbf{x}_k\right], \end{aligned} \quad (6)$$

In the notion of the deep unfolding based on the equation 6, each iteration is the combination of the terms X_k, H^T y, and $H^T HX_k$. The basic detection network [4], has been enhanced with by uplifting the dimension of the input to the higher order in every iteration and standard non-linearities are applied. Due to issues such as vanishing gradients, saturation of activation functions, sensitivity, and others, training deep neural networks is a time-consuming process [9]. During the training phase, the gradient step size K changes. As a result, the following architecture emerges:

$$h_k = \hat{x}_{k-1} - \delta_{1k} H^T y + \delta_{2k} H^T H X_{k-1}$$

$$q_k = \delta_{3k} h_k$$

$$Z_k = \rho\left(W_{1k}\left[\frac{q_k}{V_{k-1}}\right] + b_{1k}\right)$$

$$\hat{X}_{oh\,k} = W_{2k} Z_k + b_{2k}$$

$$\hat{X}_k = f_{oh}(\hat{X}_{oh\,k})$$

$$\hat{V}_k = W_{3k} Z_k + b_{3k}$$

$$\hat{X}_0 = 0$$

$$\hat{V}_0 = 0 \qquad (6)$$

With the trainable parameters,

$$\theta = \{W_{1k}, b_{1k}, W_{2k}, b_{2k}, W_{3k}, b_{3k}, \delta_{1k}, \delta_{2k}, \delta_{3k}\}_{K=1}^{L}$$

The weights and biases are modified in the training phase by the parameters W, b. ρ represents the Rectified Linear Unit Function. All such units shown in the figure 6 are stacked one on another and each iteration in the deep unfolding architecture is considered as a layer and the weighted sum of previous output are passed as input to the subsequent layers in the further iterations. [10] presents the significance for merging machine learning, specifically deep neural networks (DNNs), with channel model-based symbol identification techniques. [11] presents the deep learning-based framework for the estimation of channels in OFDM systems where the optimal weight of the network is dependent on the value of SNR which requires to re-train the network for each SNR value which would be impossible because SNR values may not be discrete.

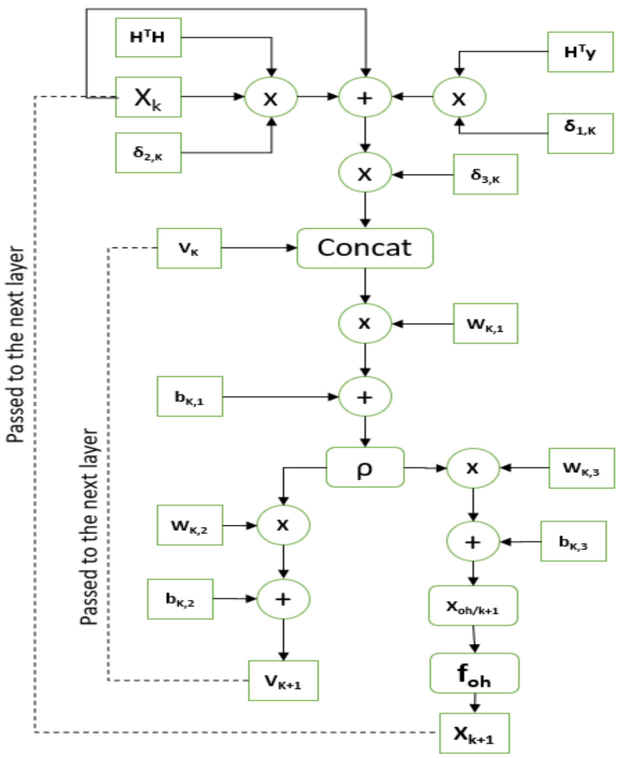

Fig. 6. k^th Layer of Detection Network

We have trained this neural network algorithm based on a MIMO channel with $K = 30$ input size and $N = 60$ output size. The neural network layers has been designed with 50 layers of Detection Network and consisting of 2*K size of auxiliary variable at each layer. It was trained over 200 iterations with a batch size of 5000 batches. The data has been generated with a generator function that returns all the required parameters for equation 5.

6. RESULT ANALYSIS

The Bit Error Rate (BER) is a crucial measure of the detection algorithm's performance. The bit error rate (BER) is the number of mistakes per unit of time. It is the number of accurately identified bit mistakes divided by the total amount of transmitted bits over a certain time span. The signal to noise ratio measures how strong the intended signal is in comparison to the noise. It is the decibel ratio between the intended signal intensity and the noise strength (dB). There is less computational complexity in a Single Input Single Output system since there is only one transmitter to broadcast the signal and one receiver to receive it. However, in a MIMO system, there would be several transmitters sending the signal and multiple receivers receiving it.

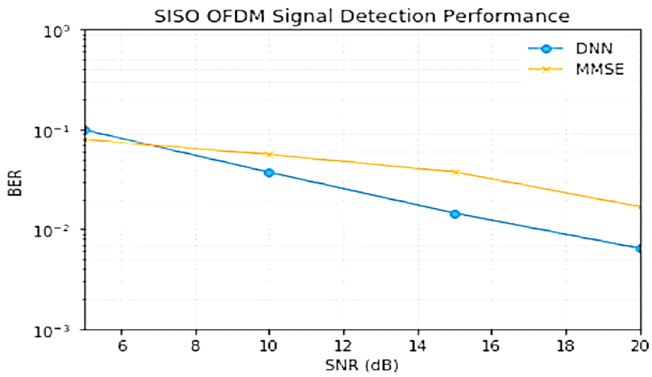

Fig. 7. SISO OFDM Signal Detection Performance

The figure 7 shows the Single Input Single Output OFDM Signal Detection performance by comparing it with the traditional MMSE signal detection with the deep learning technique using Artificial Neural Networks (ANN) algorithm. The figure 7 illustrates the graph plotted for BER with various values of SNR. It can be observed that the deep learning algorithm has given less bit error rate when compared to the traditional MMSE signal detection method. It can be noted that, this deep learning algorithm can provide better signal detection with reduced bit error rate even at the low SNR's where the strength of the signal is very less and the strength of the noise if very high. In general, the real world channel could have very high noise that impacts the signal decoding at the receiver end. The single base algorithm implemented in [15], produces the detectors of type homogenous and improves the error performance without extra antennas but, the error performance is not much higher than the traditional ML detection in linear MIMO systems.

We demonstrate the advantages of our proposed detector for MIMO with deep neural network algorithm using detection network. This kind of MIMO channel has a considerable influence on performance, as shown in the below figure.

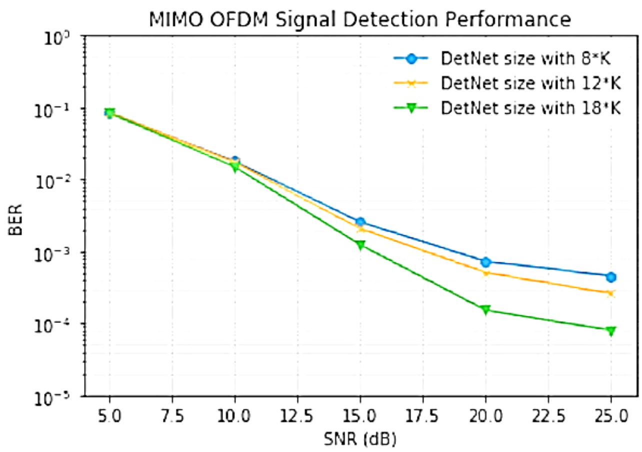

Fig 8. MIMO OFDM Signal Detection Performance

Figure 8 shows the MIMO OFDM signal detection performance by comparing it with the traditional MMSE method, deep neural network using detection network algorithm with 8*K, 12*K, 18*K size hidden layers where K is the size of transmitted symbols. The bit-error rates of various methods are compared to those of previous techniques at various signal-to-noise ratios after it has been trained using neural network. The figure 8 illustrates the graph plotted for BER with various values of SNR for various signal detection methods. It has been found that the more hidden layers the model has, the more it can learn during the training phase. It is analysed that, neural network signal detection method resulted in less bit error rate when compared to any other traditional methods.

It is observed that on increasing the number of hidden layers the learning ability of the neural network has been increased and hence detection ability of the algorithm increased. As seen in Figure 8, this resulted in a lower bit error rate. It has also been found that, in addition to reducing bit error rates and improving signal detection accuracy, the computing complexity of MIMO signal detection might be enhanced when compared to classic detection methods. But using this deep neural network architecture with MIMO OFDM, it resulted in better accuracy in signal bits detection besides reducing the burden of computational complexity and training resources.

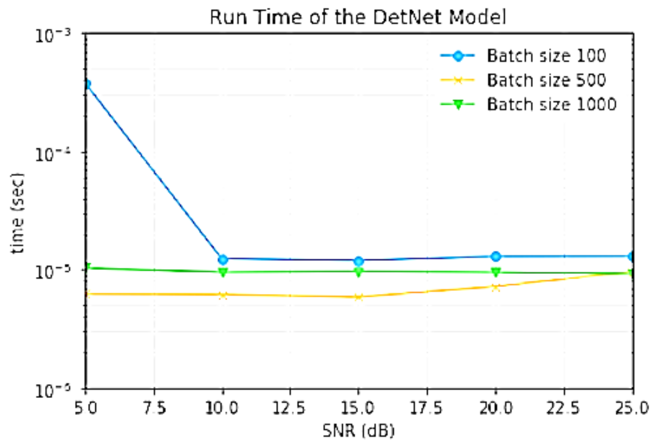

Fig 9. Run Time of the DetNet Model

The figure 9 shows the Run time complexity of the DetNet Model with varying batch sizes during the training phase across the SNR range 5dB to 25dB. The model with the batch size 100 took more time comparatively especially at low SNR as the learning is critical. Overall, the run time complexity of order 10^{-5} sec could be observed in this detection network model.

7. CONCLUSION

We have provided deep neural detection network added with standard non-linearities and enhanced dimensions of inputs as a framework for MIMO OFDM Signal detection in this paper. We examined the performance of our deep learning algorithm with MIMO within the SNR range 5dB to 30dB, which is the most critical range for the detection of the transmitted bits at the receiver end. Within any range of the SNR values, the deep learning architecture with MIMO we proposed has proven to be computationally economical and has near-optimal accuracy. The system ability to optimize over a distribution of SNR range rather than at a single SNR value makes it robust and allows it to be used in applications where the noise in the channel is varying. The system succeeds in generalizing and detecting accurately over channels with distinct characteristics from those utilized in the training phase of model, according to simulations. The traditional technique performs the not so better since no prior channel statistics are used in the detection. The simulation results show that when wireless channels are complex by significant distortion and interference, the deep learning technique has an advantage, proving that DNNs can recall and analyse tough wireless channel features. The deep neural network model must have strong generalization ability in real-world applications in order to continue to function effectively even when the conditions of online deployment do not completely match the channel models utilized in the training stage. In conclusion, a unique deep neural network model which can detect the received bits at the receiver end has been built, simulated, and verified with the graphical plots of bit error rate for wide range of SNR values.

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