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Deep Learning Based Channel Estimation for MIMO-OFDM System with Modified ResNet Model

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Abstract

Objectives: The effectiveness of wireless communication systems is significantly influenced by channel estimation. In order to accurately estimate the Channel Impulse Response (CIR) of the channel under varied circumstances, channel estimation is a crucial procedure in the functioning of MIMO-OFDM (Multi-Input and Multi-Output – Orthogonal Frequency Division Multiplexing) systems. **Methods:** The proposed Deep Learning(DL) based Convolutional Neural Network (CNN) with modified ResNet architecture channel estimation method improves the Bit Error Rate(BER) and Mean Square Error(MSE) performance compared to conventional channel estimation methods. We have compared the proposed CNN method with the Least square (LS), Minimum Mean Square Error(MMSE) and Deep Neural Network(DNN) based channel estimation methods. The results have been discussed by using BER and MSE versus SNR graphs. The simulation results are being performed on the MATLAB platform of the R2021b version. **Findings**: The DL-based MIMO-OFDM channel estimation can achieve better performance over multipath fading channels if Channel coefficients are perfectly estimated at the receiver. The simulation test is carried out in different test conditions by considering the different number of transmitter and receiver antennas with respect to different QAM modulation order values. **Novelty:** The DL-based modified ResNet architecture comprises a set of layers modified to estimate the optimal channel parameters. For achieving a great reduction of MSE and BER compared to conventional channel estimation methods, the layers of the ResNet– model are modified.

Keywords: Channel estimation; MIMOOFDM system; Deep learning; Neural network; ResNet

1 Introduction

Future wireless communication systems must be capable of handling increased data speeds, dependable transmissions, and bandwidth efficiency. In the presence of multipath channel propagation, the link reliability and system capacity can be boosted by using MIMO systems, which can able to provide bandwidth efficiency for large data rates. In these systems, multiple antennas are utilized at both transmitter and receiver need a challenging method of channel-equalization for a frequency-selective broadband channel to minimize the intersymbol interference (ISI). An OFDM method uses for MIMO to resolve this problem. Acquiring accurate channel state information (CSI)through channel estimation is a prerequisite for realizing the huge potential of MIMO-OFDM technology, and it is also an important basis for realizing precoding, resource allocation, signal detection, indoor positioning, physical layer security, and so on [1] .

In MIMO-OFDM, numerous channel parameters need to be estimated because of the many transceiver antenna pairs. Conventional channel estimation algorithms will result in enormous pilot and feedback overhead for massive MIMO systems, as well as a severe loss of performance in both spectral efficiency and complexity, limiting the application. With the in-depth research of massive MIMO-OFDM channels, the performance enhancement of current optimization algorithms based on ideal assumptions and model approximation tends to saturate in increasingly complicated application scenarios.

It is clear from this that channel estimation based on deep learning(DL)provides a new idea to break through this bottleneck. Deep learning Provided excellent performance in computer vision, natural language processing, and automatic speech recognition. A technological revolution is also brought by deep learning in the techniques, patterns, and ideas of wireless communication systems [2,3] . The two major reasons are encouraged to use the DL in various fields [4] . The primary benefit is better detection of flaws in real-world systems based on DL algorithms and the second one is that they include basic operations like matrix-vector multiplications. In wireless communications, DL was introduced as a physical layer because of these benefits and implemented in numerous applications [5,6] .

One of the well-researched issues is the channel estimate among all DL applications of wireless communication systems. In [7] , a Learned Denoising-based Approximate Message Passing (LDAMP) network was utilized for designing a receiver based on a limited number of radio-frequency (RF) chains in massive beam space millimeter wave (mm-Wave) MIMO systems.

In [8] , signal transmission and reception are considered to deal with the end-to-end DL architecture while considering a communication system as a black box. The fully connected Deep Neural Network (FC-DNN) is used in this technique to learn about the frequency selective wireless channels' features and counteracting non-linear interference and distortion in OFDM systems. This method is specifically ineffective for applications that need full channel response due to that it can't determine the channel time-frequency response directly. In [9,10] , the CsiNet-LSTM and CsiNet networks were proposed to provide CSI feedback in massive MIMO systems. These systems are facing challenges relevant to channel estimations and direction-of-arrival (DoA). These issues are addressed using a novel approach in [11] by implementing DL methods for MIMO systems.

In [12] , DL-based channel estimation extends to selective channels that have been shown to provide better performance than traditional estimations in various cases. This method includes three phases, such as (i) pre-training that focuses on getting an initialization of the DNN weights desirably; (ii) offline training, in which the DNN is taught on known data for learning about channel estimation; and (iii) online testing, where the testing of DNN is done over unknown data.

In [13] , the DL method is used to estimate the channel based on an image super-resolution and denoising method while considering a channel matrix as an image. A higher potential of using the frequency, temporal, and spatial correlation of neighboring channel elements has been included in the convolutional neural networks (CNNs). When compared to the traditional approach of MMSE, better performance is achieved using the CNN-based CE. In [14] , the authors suggested using a DNN model to conduct channel estimate for the IEEE 802.11p standard by utilising the channel correlation in both the time and frequency domains.

The authors of[15] suggested ChanEstNet, a DL-based channel estimation network only suitable for SISO-OFDM systems. Even though ChanEstNet outperforms conventional methods of channel estimation, it is limited to SISO-OFDM and block pilot pattern systems. In [16] , the authors demonstrated the utilization of a trained model for deep neural network (DNN) that integrates with the pilot signal to compute the underwater channels with accuracy. In [17] , a wireless energy transfer system was used based on a deep autoencoder using CE and provided the results for the phase of channel estimation. The feedback regarding the energy data is collected based on a channel estimation of the downlink.

In time-varying channels [18,19] , the decision-directed channel estimates can be improved using the DNNs. In [20] , the CE and pilot design are optimized jointly for addressing the case, in which the total number of antennas is greater than the pilot length for all user terminals. By comparing with the conventional MMSE approach, the spatial-frequency (SF) CNN (SF-CNN) can be outperformed in terms of estimate performance for mmWave MIMO systems [21] while achieving the less complicated systems.

It has been observed from the above literature that the traditional pilot based channel estimation techniques in MIMO-OFDM shows the poor performance in time varying channels and computational complexity will be more. The most of the authors only considered channel estimation in SISO-OFDM systems using deep learning algorithms. In this Paper In this paper, we extend our preliminary work [8,13] , which only used a fully-connected deep neural network (FDNN) model to enhance the channel estimation of a SISO-OFDM system over frequency-selective fading channels. We show the system performance of the proposed deep learning-based channel estimation framework with different combinations of transmitter receiver antennas and various order of modulation. Our main contributions are summarized as follows:

• By comparing with the conventional methods like LS and MMSE estimators, the DL-based channel estimation system performance is analyzed. The DL estimator can be approximated by the MMSE and LS estimators accurately by establishing ReLU CNNs.

• A CNN model is proposed based on a modified architecture of ResNet for the estimation of a channel by implementing a novel training strategy.

• To study the effectiveness of channel estimation and the effects of different modulation schemes, the experiments were performed using 32-QAM and 16-QAM for different receiver and transmitter antennas.

Section II describes a system model based on channel estimation in comparison with the traditional approaches. Section III demonstrates a proposed DL-based channel estimator structure and network training while Sections IV and V presented the simulation results and conclusion of the proposed method, respectively.

2 Methodology

Figure 1 displays the system architecture for MIMO-OFDM is presented with the transmit antennas of ‘Nt’ and the receiver antennas of ‘Nr’. Prior to the signal transmission to the serial to parallel converter, a constellation modulation block is used while modifying the input bits at the transmitter. In a sub-frame, the ‘M’ OFDM symbols and ‘N’ subcarriers are assumed. The frequency doma$X_m^j(k)$n symbol i on jth ante^{nn}a with mth OFDM symbol and kth sub-carrier transforms into the time-domain symbol after performing the Inverse Fast Fourier Transform (IFFT). It is formulated as follows:

$$X_m^j(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} X_m^j e^{\frac{j2\pi kn}{N}} \quad for\, k = 0,1,2,3....N-1 \tag{1}$$

Once the time domain symbols of OFDM are passed via a parallel to serial converter block by adding the cyclic prefix to suppress inter-symbol interference (ISI) as a guard interval, they have been sent on the transmit antenna. During the channel propagation, the multipath fading and additive white Gaussian noise (AWGN) impact the transmitted signal. It’s difficult for demodulating the sent symbols approximately due to the multipath channel

The modelling of a MIMO frequency selective channel has been considered as:

$$y^i(n) = \sum_{j=1}^{t} \sum_{l=0}^{L-1} h_{ij}(l)\, x_i(n-l) + V_i(n) \tag{2}$$

i= receive antenna

j=transmit antenna

L= number of taps of frequency selective channel

$V_i(n)$ =AWGN Noise

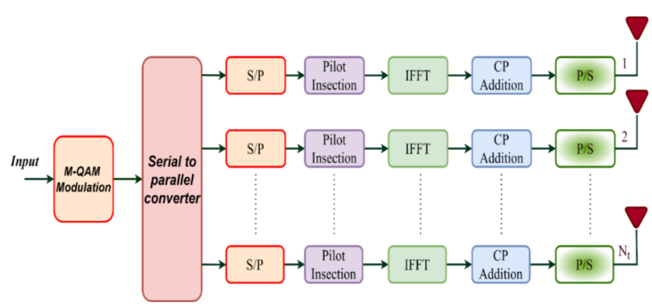

Fig 1. MIMO-OFDM Transmitter

At the OFDM system output, the cyclic prefix is resulted in the circular convolution. The received signal of OFDM y^i upon the receiver antenna of i at the receiver is denoted as:

$$y^i = \sum_{j=1}^{t} h_{ij} \otimes X_j + V_i \tag{3}$$

$\otimes$denotes Circular Convolution

In the serial to the parallel block, the received serial symbols of OFDM systems convert into the parallel and removed the cyclic prefix as shown in Figure 2 . The conversion of the k^{th} subcarrier, the m^{th} OFDM symbol is performed into the frequency domain symbol $Y_m^i(k)$ after completing the operation of fast Fourier transform (FFT) at the output time domain symbol on the ith antenna:

$$Y_m^i(k) = \sum_{j=1}^{t} H_{ij}(k) X_j(k) + V_i(k) \tag{4}$$

$Y^i(k)$ is the k^{th}FFT point of $[y_i(0),\ y_i(1) - - - - - - - - - y_i(N-1)]$

$X^j(k)$ is the k^{th} FFT point of $[h_{ij}(0),\ h_{ij}(1),\ h_{ij}(L-1),\ 0 - - - - - - 0]$

$Y^i(k)$ = The received symbol at the i^{th} receiver antenna and kth subcarrier.

$X^j(k)$ = The transmitted symbol for j^{th} receiver antenna and on the kth subcarrier.

$H_{ij}(k)$ = The channel coefficient of the kth sub-carrier between receiver transmit antenna pair of (i,j).

However, each sub-carrier is a flat fading channel of MIMO system and the system model can be written as:

$$\begin{bmatrix} y_1(k) \\ y_2(k) \\ \vdots \\ y_r(k) \end{bmatrix} = H_{r\times t} \begin{bmatrix} x_1(k) \\ x_2(k) \\ \vdots \\ x_t(k) \end{bmatrix} + \begin{bmatrix} v_1(k) \\ v_2(k) \\ \vdots \\ v_r(k) \end{bmatrix} \tag{5}$$

Where the rxt channel matrix is given as

$$H = \begin{bmatrix} H_{11}(k) & H_{12}(k) & \dots & H_{1t}(k) \\ H_{21}(k) & H_{22}(k) & \dots & H_{2t}(k) \\ \vdots & \vdots & & \ddots \\ H_{r1}(k) & H_{11}(k) & \dots & H_{rt}(k) \end{bmatrix} \tag{6}$$

$H_{ij}(k)$ is the channel coefficient between i^{th} receive antenna and j^{th} transmit antenna on the k^{th} subcarrier

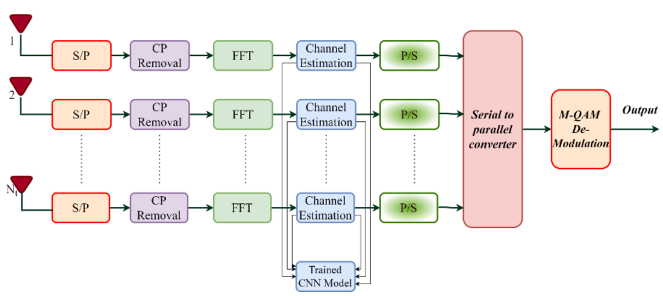

Fig 2. MIMO-OFDM Receiver

To acquire the channel matrix H_{ij} (k) using a receiver, the channel estimation method is used based on the known values of $Y^i(k)$ and $X^j(k)$. Through the estimated channel matrix, the symbol received from each antenna is sent to parallel to the serial converter. Finally, output bits are obtained by constellation demodulation.

2.1 Conventional Channel Estimation

As mentioned in (5), channel estimation aims to determine the parameters of a channel from a received signal. The channel coefficient ‘h’ is required to be known for detecting the transmitted signal x(k) at a receiver. In general, the training or pilot symbols are used for computing channel estimation. However, these symbols are known for both the transmitter and receiver.

As the wireless receiver programs before, the set of symbols is known. For determining the unknown fading channel coefficient, the output is observed at the receiver in relevant to the transmitted pilot symbols. Numerous approaches of interpolation like spine cubic interpolation, second order interpolation, and linear interpolation are used to estimate the channel responses for all subcarriers between pilot symbols once the estimation of channel state is obtained at the pilot symbols.

The widely used conventional channel estimation technique is the least square algorithm that includes a problem of channel estimation is

$$\begin{aligned} \left\|Y^T - X^T H^T\right\|^2 &= \left(Y^T - X^T H^T\right)^T \left(Y^T - X^T H^T\right) \\ &= Y^T Y - Y^T X H - X^T H^T Y + X^T H^T X H \end{aligned} \tag{7}$$

To find the minimum value of function we must set the first derivative of the function to equal to zero therefore

$$\begin{gathered} \frac{\partial}{\partial H}\left(Y^T Y - Y^T X H - X^T H^T Y + X^T H^T X H\right) = 0 \\ \widehat{H}_{LS} = Y X^T \left(X X^T\right)^{-1} \\ \text{We get } \widehat{H}_{LS} = X^{-1} Y \end{gathered} \tag{8}$$

Due to its simplicity, low complexity, and lack of channel information, the Least Squares channel estimator is frequently used for channel estimation. The square distance minimizes between transmitted symbols (X) and received symbols (Y) and it is determined. In time varying channels, the performance of the algorithm is analyzed and showed poor outcomes.

The MMSE algorithm was designed by using the estimation and mean square error of a real channel to limit the noise-sensitive issues for the LS method. The MMSE estimation is created as shown in the below equation by combining the results of the least square channel estimate in (8).

$$\widehat{H}_{MMSE} = R_{H\widetilde{H}} \left(R_{HH} + \frac{\sigma_n^2}{\sigma_x^2} I\right)^{-1} \widehat{H}_{LS} \tag{9}$$

Where, $R_{HH} = E\{HH^H\}$ is the autocorrelation matrix for channel response in the frequency domain, $\sigma_n^2 \& \sigma_x^2$ refer to the variances of Additive white Gaussian noise and transmitted signal, respectively, H_{LS} is the cross correlation matrix between temporary and actual estimated channels. As the MMSE estimator is required some prior knowledge about the channel's statistical characteristics like noise variance and a channel autocorrelation matrix, it's difficult to use when compared to the LS estimator. For enhancing the channel estimation accuracy, the MMSE approach takes noise into account.

2.2 Proposed Deep Learning-Based Channel Estimation

It's essential to indicate that recent research is achieved better results like more abstract features can be learned by deep networks. Adding layers to a deep neural network makes training more difficult, and accuracy begins to saturate and then degrade. The value of the product of derivatives decreases as the number of layers in the network increases until the partial derivative of the loss function approaches zero and disappears. This is referred to as the vanishing gradient problem. As a result, the weights cannot be updated. To solve the vanishing gradient problem, we propose a different enhanced CNN architecture with a residual network called ResNet.

Modern architecture ResNet offers improved capabilities of feature extraction for different applications. However, the ResNet architecture's use of identity or skip connections between stacked convolutional layers is more significant shown in Figure 3 . These shortcut connections restrict the problems of vanishing gradient in training the deep architectures while allow the gradients for spreading over identity connections.

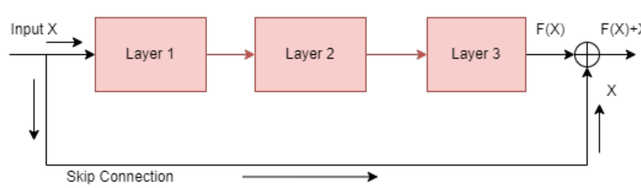

Fig 3. Residual Learning:a Building Block

2.3 Network Structure

As shown in Figure 4, the proposed pipeline is demonstrated for DL-based channel estimation, known as ResNet. The main objective is to determine the channel coefficients in the MIMO-OFDM system. The expression deep learning usually refers to neural networks that are made up of a series of layers. The result of the layered organization of neurons is the ability of the learning network to analyze data hierarchically. The first layers see raw data, and each subsequent layer is able to use more information from the neurons of the previous layer for processing. The layers in the proposed modified ResNet are depicted in Figure 4.

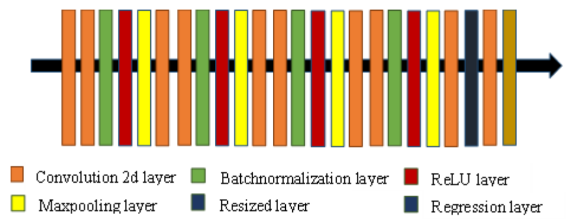

Fig 4. Layersin Modified ResNet model

The proposed model comprised with 10 convolution 2d layers, 1 regression layer, 1 resized layer, 4 maxpooling layers, 4 ReLU activation layers, and 4 batch normalization layers. Different networks include a single output layer and a single input layer. Designations simply define the position of a layer within the multiple layers: the input is the start and the output is the end layers. The proposed deep learning based model is divided into two stages: Training and working. In the training stage, the optimal channel parameters are calculated based on the modified ResNet model. Once training is completed, the network model is stored and it is furtherly used in the working stage. To validate the proposed channel estimation technique, the trained network model applies with input data in the working stage. The accuracy of the system is depended on the layers of the network model. In this proposed work, the layers of ResNet model are configured to obtain better optimal values and the functionality of each layer used in this ResNet model is explained as follows:

2.3.1 Input and output layers

The input layer is usually not shown in a deep learning architecture diagram. It is simply a memory that holds the input data. It can be thought of simply as some collection of memory cells, each of which stores a single input number. In the output layer, the network results interact with the outside world.

2.3.2 Convolution layer

To gain the advantages of inter-antenna and inter-frequency correlations, the convolutional layers are utilized for improving the estimation performance of the proposed NN architecture. The complex signal is divided into the imaginary and real parts prior to the implementation of the Convolutional neural network as the neural network supports the real format only while the signal of the MIMO-OFDM system is in the complex format. For interpolation of the frequency domain, the first two layers of CNN are used primarily and are followed by an independent operation of 2D convolution. A set of weights is used to link the several parallel filters of a typical CNN to a local patch of input data. The data traverse in two dimensions vertical and horizontal directions using these filters for computing the convolutional products. However, the convolution filter is assumed as ‘W’ which applies to the data that is convolved through the sliding of a filter across data and the output of convolution obtains based on weighting the data sum. The convolutional neural network with a transformation formula is expressed as:

$X' = f(W*X+b)$

Where X is convolutional data, b refers to the offset vector, ‘*’ is the convolution operation, and f(.) refers to the activation function. However, the ReLu activation function is used in this paper.

2.3.3 Batch normalization layer

The quantities of a computational layer like a convolution layer are modified using the batch normalization layer. It collects together all the quantities coming out of the layer as a group. It then normalizes all the values so that they all have a standard deviation of 1 and mean of zero. This prevents the output values from moving into either a very positive or very negative region or excessive expansion (or contraction). This action helps to keep the values closer to the region where the activation function has the most useful nonlinearity. In short, the batch normalization layer seeks to modify the moving data to regularize the network or keep the weights small.

2.3.4 ReLU layer

ReLU (Rectified Linear Unit) is a nonlinear activation function expressed as $f(v) = max(0, v)$. For a neural network with a large number of network layers, the traditional activation function such as the Sigmod function will cause the problem of gradient disappearance during reverse calculation because the derivative value at both ends tends to the 0. The derivative of the ReLU function is 1 when > 0, so that the training of the deep network can be completed more effectively. The computational complexity of the ReLU function is relatively small. When calculating the gradient in the backpropagation process, the traditional activation function has a large amount of calculation, while the ReLU function only needs to use simple calculation methods such as comparison, which saves a lot of time. The ReLU function is a unilateral suppression function (when <0, the value of the ReLU function is 0), which will make the output of some neurons in the network to be 0, so that the network with sparseness can alleviate the problem of overfitting happened.

2.3.5 Maxpooling layer

The original data of the input layer will get a feature map after passing via an activation layer and a convolution layer. More redundant data is contained in the feature maps and the information extracts are based on a pooling layer, which is responsible to filter out the feature data and eliminate the redundant information. However, the pooling layer refers to the filter as it filters the most representative information of feature data. In the pooling box, the maximum value retains in the max pooling only so the most representative data can be extracted effectively using the max pooling in the feature map.

2.3.6 Resized layer and Regression layer

In Resized layer, the input data is resized to the target size. Resized layer allows us to change the size of the data passing through the network. This process is often used for data when we want to reduce the size of the data so we can process it faster. In the Regression layer, the input data as the half mean squared error loss.

2.3.7 Pruning

In the proposed model of the deep neural network, each node is tightly connected. The method of reducing the number of parameters by deleting the connection between the nodes where the weight is small or deleting the node with a small impact is called pruning. Reduce the number of parameters by removing nodes and weights. By reducing the parameters that need to be remembered, the number of calculations is reduced and memory usage is reduced. As a result, one can expect to reduce the weight of the model and speed up the processing. Various techniques have been proposed as to which connection to delete. In some cases, Pruning can remove 80% to 90% of connections. In general, pruning alone will reduce the accuracy, so re-learning after pruning will maintain the original accuracy. Quantize is a method to reduce the weight of a model by expressing parameters such as weights with smaller bits. By limiting the bits used, you can reduce memory usage without changing the structure of a network.

2.4 Network Training

To accurately predict the channel parameters during the network model operation, the learning error with backpropagation and training symbols should be trained primarily as shown in Figure 5. The training process of a proposed model with summary is presented.

The neurons in the hidden layers initially deal with the training input data, which is then transmitted to the output layer. When results don't match with the desired ones at the output layer, the learning errors will be tracked backward from the output to the hidden layers. These errors are existed between target outputs and network outputs. Thus, the biases and weights of neurons will be adjusted. Until the requirements are satisfied, like the predetermined number of iterations, the procedure of training will be repeated.

During the models' training, the wireless channels and modulation of MIMO-OFDM systems can be treated as 'black boxes'. In a simulation, the models of multipath fading channels can be utilized for collecting the training data. The transmitted symbols can be generated randomly in each simulation while creating the corresponding frame of OFDM based on a series of pilot symbols that should be fixed over the deployment and training phases. For the simulation of a current random channel, the models are used. The OFDM frames are used for a current channel distortion that includes channel noise for a received signal of MIMO-OFDM systems. In the training data, the original transmitted and received signal data are included. The received

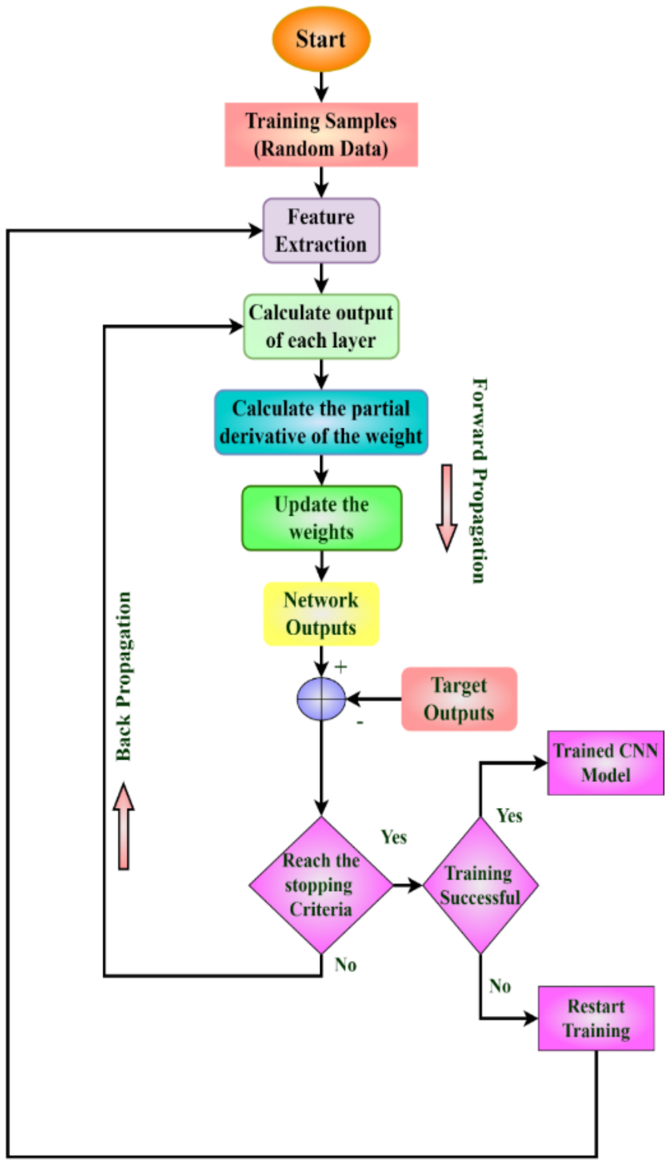

Fig 5. The training process of the proposed CNN model. The main objective is to reduce the error between outputs of a network and the desired outputs of finding the appropriate weights and biases for a CNN's training with theResNet architecture

data from data and pilot blocks are considered as input for a deep learning model. The difference between transmitted data and a neural network output is minimized based on the trained model. We use a total of the data set containing two distinct categories, such as 70% and 30% of the data for training and testing, respectively, from 250000 training samples used to train and test the ResNet model. The number of total epochs is 100, the size of the mini-batch is 128, the learning rate is 0.001 and the optimizer is Adam with a validation frequency of 300. Table 1 shows the Simulation Parameters of the MIMO-OFDM System.

3 Results and Discussion

This section discusses the simulation results for a proposed channel estimation technique using the deep learning method for the MIMO-OFDM system. The proposed method's performance is evaluated in terms of Bit Error Rate (BER) and Mean Square Error (MSE) in comparison with other existing channel estimation techniques like the deep learning with deep neural network, MSME method, and LS method for single input and single output OFDM systems [8,13]. The conventional deep learning based interpolation channel estimation methods failed to provide a better reduction in BER metric values. The proposed method was

Table 1. Parameters of MIMO-OFDM System

Parameters	Specificaions
QAM order	16/32 QAM
subcarrier spacing	15 kHz
Number of subcarriers	72(Data: 64 and pilot:8)
Type of Channel	Rayleigh fading- Multipath
SNR	0 to 20 with step size: 5
Length of Cyclic Prefix	36
No of symbols	300
No of frame each SNR	5000
No. of Transmitted antennas (Nt)	2/4/8
No. of Received antennas (Nr)	2/4/8

tested based on considering different configuration parameters.

3.1 Simulation Results under Scenario 1

The proposed deep learning-based channel estimation method's viability is shown based on simulation studies that evaluate the proposed approach of channel estimation based on robustness. If number of receivers (Nr) and a number of transmitters (Nt) are equivalent to two, the BER and MSE performance achieves with SNR for 16-QAM and 32-QAM as shown in Figures 6 and 7. The best performance of mean square error at all values of SNR is achieved by using a proposed ResNet-based channel estimation when compared to the channel estimation methods like deep learning with DNN, minimum mean square error (MSME), and least squares (LS) method as shown in Figure 6 (a) and (b). The reduction of BER and MSE is achieved by using the proposed channel estimation method if a SNR value is higher. The MSE performance improves using 32 QAM than the MMSE, LS, and the methods in [8,13].

As shown in Figure 7 (a) and (b), the BER performances are compared for different orders of QAM modulation if the number of receivers and transmitters is equal to two. However, the performance improves for the proposed method of channel estimation. The results of increased BER performance are achieved with the increased modulation order.

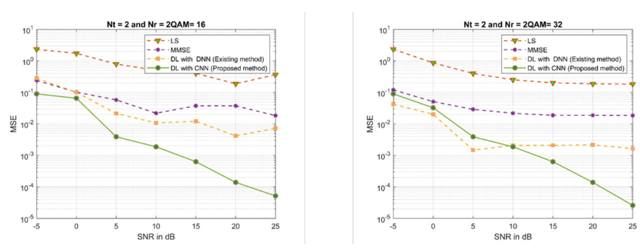

Fig 6. MSE Comparison results of proposed method with N_t=2 and N_r=2 with 16/32 QAM.a) MSE comparison results of proposed method with Nt=2 and Nr=2, 16-QAM. b).MSE comparison results of proposed method with Nt=2 and Nr=2 32 QAM

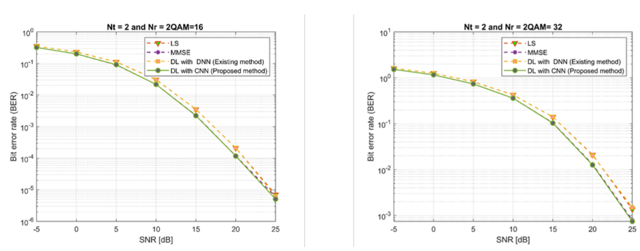

Fig 7. BER Comparison results of proposed method with Nt=2 and Nr=2 with 16/32 QAM. a) BER comparison results of proposed method with Nt=2 and Nr=2, 16-QAM. b) BER comparison results of proposed method with Nt=2 and Nr=2, 32 QAM

3.2 Simulation Results under Scenario 2

The proposed channel estimation method and the MMSE and LS channel estimation techniques were compared based on BER and MSE. But here the number of transmitters and receivers is four. Figure 8 (a) is showed the proposed channel estimation results in terms of better MSE value compared to the LS, MMSE and channel estimation techniques proposed in (8,13) for all the value of SNR. But for the 32 QAM technique, the proposed technique exhibits a slight increase in MSE value for small SNR value compare to (13). When the SNR value is 0 the performance of the proposed technique and MMSE is same. But for higher SNR values the proposed technique exhibits a significantly lower value of MSE as shown in Figure 8 (b).

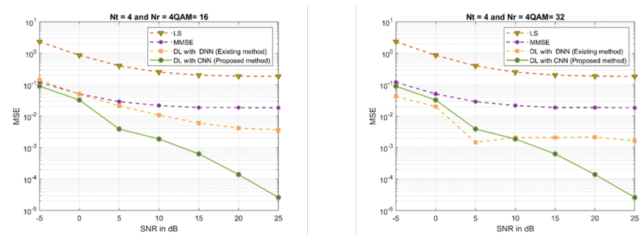

Fig 8. MSE comparison results of proposed method with Nt=4 and Nr=4, 16/32 QAM. a) MSE comparison results of proposed method with Nt=4 and Nr=4, 16-QAM. b) MSE comparison results of proposed method with Nt=4 and Nr=4 32 QAM

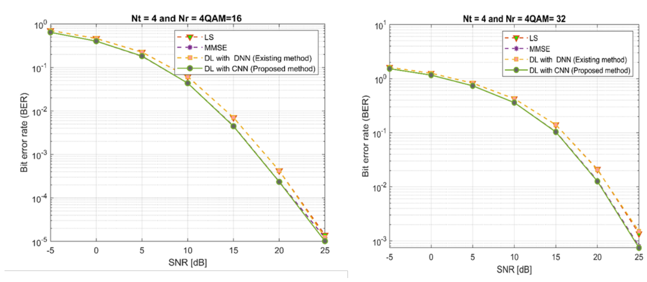

Fig 9. BER Comparison results of proposed method with Nt=2 and Nr=2 with 16/32 QAM. a) BER Comparison results of proposed method with Nt=4 and Nr=4, 16-QAM. b) BER comparison results of proposed method with Nt=4 and Nr=4 32 QAM

In Figure 9 the BER Performance of Proposed method improves compared to conventional and existing methods in (8,13) but the BER performance under Scenario 2 increases compared to Scenario1.

3.3 Simulation Results under Scenario 3

The number of transmitters and receivers, in this case is, 8. As shown in Figure 10 (a) and (b), the proposed channel estimation had a lower MSE value than the LS and MMSE for all SNR values for the 16 QAM technique except when the SNR value is -5, at this value the performance of proposed technique and MMSE is the same. When compared to channel estimation techniques proposed in (8,13), the proposed technique has a slight increase in MSE for very few lower SNR values. However, for higher SNR values the proposed technique has a significantly lower MSE value. For the 32QAM technique, the proposed method performance is similar to scenario 2. When BER is compared to SNR, the proposed channel technique employing 16QAM modulation outperforms the LS, MMSE, and channel estimation techniques proposed in (13), as illustrated in Figure 11. Compared to BER performance under scenarios 1 and 2 the BER performance under Scenario 3 increases.

Figures 6, 7, 8, 9, 10 and 11 show the results for the pilot-based channel estimation method, the ResNet model is used to replace the original classifier, which greatly improves the MSE and BER reduction; when the channel is known, the MSE and BER reduction of the proposed ResNet model can approach the theoretical value, and even the BER of the neural network model will be slightly better than the theoretical value on individual SNR values. The experimental analysis shows that the model can predict values that have not appeared in the training set and the strong robustness of the model, which is equivalent to a certain correction ability when discriminating the original data. The requirements of learning accuracy for neural networks are improved in the modulation order. By comparing with the channel estimator based on a lower modulation order, it's complex to make the classification of a received signal for different points of constellation based on a channel estimator with a higher

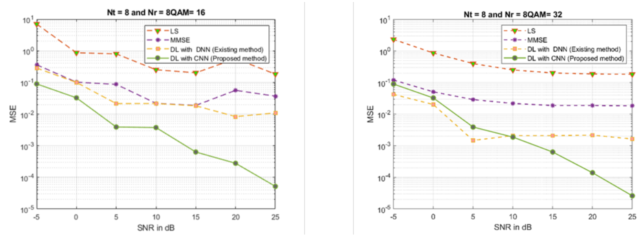

Fig 10. MSE comparison results of proposed method with Nt=8 and Nr=8,16/32 QAM. a) MSE comparison results of proposed method with Nt=8 and Nr=8, 16-QAM. b) MSE comparison results of proposed method with Nt=8 and Nr=8, 32 QAM

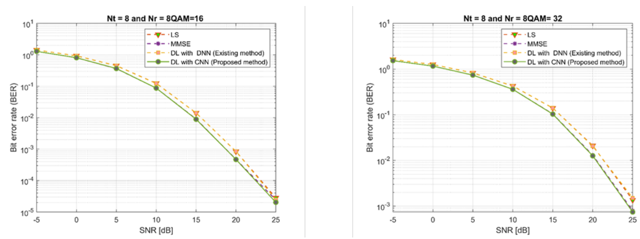

Fig 11. BER comparison results of proposed method with Nt=8 and Nr=8, 16/32 QAM. a) BER comparison results of proposed method with Nt=8 and Nr=8, 16-QAM. b) BER comparison results of proposed method with Nt=8 and Nr=8, 32 QAM

modulation order.

4 Conclusion

In this paper, channel estimation is performed on the received data symbols and combined with the MIMO-OFDM system and the ResNet network model, a complete simulation system is built. The improved ResNet network model is suitable for time-variant and additive white Gaussian noise channels based on Rayleigh fading multipath channels. The conclusions are (1) Out of four channel estimation techniques, Deep learning using CNN with ResNet architecture has excellent performance as it achieves the lowest BER of 0.0126 at 20dB (SNR) while it is 0.0206 for LS estimation and MSE Values of 0.0013 at 20dB and 0.1876 for LS estimation over variable SNR (2) In comparison to the Single Input and Single Output (SISO) OFDM system with traditional channel estimation techniques, the suggested method also exhibits improvement while using various orders of modulation schemes and varying numbers of transmitter and receiver antennas. The number of transmitters and receivers increases the probability of carrying more bits through the available channel as well as the likelihood of an error occurring. Using a greater number of transmitters and receivers allows for more information to be transmitted at the same time, but at the expense of a higher BER. (3) DNN based channel estimation outperforms other conventional channel estimation Algorithms. Therefore, it can be concluded that the proposed DNN model trained with Adam optimizer can be efficiently used as a channel estimator in MIMO-OFDM communication systems. Future research will focus on the computational complexity of the proposed estimator as well as the performance of the estimator using other optimization strategies. The DL estimator, however, is sensitive to the quality of training data, and its performance would be severely reduced if the distribution of data in real situations were wider than that of the training data.

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