Channel Estimation and Equalization Using FIM for MIMO-OFDM on Doubly Selective Faded Noisy Channels

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ABSTRACT

Orthogonal frequency division multiplexing (OFDM) plays an important role in wireless communication due to its high transmission rate. Information is conveyed across spatial and temporal dimensions through the space-time shift keying (STSK) technique which is basically used to handle multiplexing diversity and gains. On the other hand, index modulation integrated OFDM not only communicates information through conventional signal constellations as in classical OFDM, but also through indexes of the subcarriers. In index modulation, the subcarriers are transmitted over a particular index and can be implemented effectively. The active indices are selected and further information bits transmitted. In this paper, to handle such limitations, the deep neural network (DNN) has been proposed for end-to-end performance. Under the noisy and faded channel scenario, channel state information must be acquired to recover the transmitted signal correctly. To evaluate the channel distortion level, a deep learning model is trained offline from simulated data and then applied to online data to estimate and recover the channel state as well as the transmitted signal, respectively, in comparison to the traditional least minimum mean square error (LMMSE) channel estimation technique. The analysis results demonstrate superiority over the conventional LMMSE for channel estimation and signal detection in wireless communications with complex channel distortion and interference. The mean square error (MSE) is evaluated for carrying out performance information in each subcarrier block and to reduce the detector error rate.

Keywords: Orthogonal Frequency Division Multiplexing, OFDM, Frequency Index Modulation, FIM, Channel Estimation, Deep Neural Network, DNN, Bit Error Rate

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1. INTRODUCTION

One of the most prominent multi-functional MIMO (multiple input multiple output) techniques is space-time shift keying (STSK). The tasks of transmission diversity and multiplexing are very successfully achieved through this technique [1]. The spatial shifting key (SSK) and spatial modulation (SM) merely receive diversity gains while STSK transmits as well as receives diversity gains. This implies that the information is distributed in temporal and spatial dimensions through STSK. Traditional PSK/QAM symbols are employed to map the information and one of the dispersion matrices becomes activated for the transmission of additional information [2–5]. One of the major challenges pertaining to broadband fade channels is multipath fade distortion and this is often dealt with by multi-vector modulation. This is done by attaining a few parallel channels from dispersive broadband channels through a narrow channel with flat attenuation [6, 7]. The most commonly used MC modulation technique is the orthogonal frequency division multiplexing (OFDM) since it offers low-complexity implementation and is the most robust among the broadband channels. The OFDM is assisted by STSK to overcome the degradation of SC-STSK pertaining to broadband channels. The indexes involved in the transmitting antennas of a MIMO system are used along with constellations of conventional M-ary signals in SM. The traditional MIMO schemes depend on spatial multiplexing for data rate enhancement and spatial diversity to improve error performance. In an SM scheme, multiple transmission antennas relating to one MIMO system are employed in another ending [8, 9].

There are several channel estimation techniques such as least squares (LS) and minimum mean square error (MMSE). However, these do not work well in fast mobile conditions since they suffer many drawbacks. For instance, traditional channel estimation techniques are subject to performance degradation due to the unavailability of channel state information, or they may not be capable of handling fast-changing channel states due to mobility issues [10, 11]. Recently, many researchers have been focusing on the application of deep learning (DL) in wireless communications to achieve better performance [12–15]. Many applications such as channel estimation, channel state, data decoding, etc., are evaluated using deep learning. Traditional channel estimation techniques tend to be pilot-based and blind [16] for

OFDM and MIMO-OFDM wireless systems, respectively. The accuracy of traditional systems is low, leading to bandwidth overhead. Therefore, an accurate channel estimation technique is required that does not need any pilot information for the channel state. In this article, a deep neural network (DNN) approach is used to estimate channel state and detect transmitted data symbols in an OFDM system. Deep learning and artificial neural networks (ANNs) have numerous applications such as localization based on CSI [16], channel equalization [17], and channel decoding [18] in communication systems.

1.1 Problem Statement

Training overheads present a fundamental obstacle in the challenge of large MIMO channel estimation. The quantity of pilot sequences increases along with the number of antennas. This becomes a major issue in systems that use downlink pilots in duplexing mode because the minimum size of pilot sequences requires the generation of a least squares channel estimate, controlled by the number of pilot sequences. Furthermore, since most current wireless communication protocols are based on frequency division duplexing (FDD) and depend on the downlink channel estimate, the training overhead problem makes progress toward a huge MIMO situation difficult. For noisy and non-stationary wireless channels, channel estimation is regarded as a difficult issue for multiple input and multiple output orthogonal frequency division multiplexing (MIMO-OFDM). To address the problem, a DNN is presented in this paper to handle end-to-end performance.

This work focuses on channel estimation in OFDM systems. The main objectives of this research are:

- To review the effectiveness of frequency indexed modulation on MIMO-OFDM as a technique for wireless applications.
- To design a deep neural network-based channel estimation technique and compare its performance with other existing channel estimation techniques.
- To analyze mean square error performance for channel estimation in noisy channels.

1.2 Paper Organization

The rest of the paper is organized as follows. Section 2 describes the research contributions in this field. A brief discussion on deep learning is given in Section 3, while the system model is described in Section 4. Section 5 provides the analysis results under different conditions, while Section 6 presents the conclusion.

2. RELATED WORK

Vucetic and Yuan [1] provided information on space-time coding and its application for wireless communication systems.

Badic [3] proposed a unified theory of quasi-orthogonal space-time block codes (QSTBC) involving four transmissions and one or more receiving antennas. The main objective of this work is to provide a unified QSTBC theory for four transmission antennas and one or more receiving antennas. This paper consists of two main parts: in the first part, the QSTBC transmission without knowledge of the channel at the transmitter is analyzed, while in the second part, the transmission with QSTBC accepts information on the secondary state-channel (CSI) on the transmitter is analyzed. In both cases, the QSTBCs are examined on MIMO channels with a correlated and unrelated flat frequency using a maximum likelihood receiver and a low-complexity, zero-demand linear receiver.

Rajeswari and Thiruvengadam [5] proposed a hybrid channel estimator for a multi-input and multi-output orthogonal frequency division multiple access system (MIMO-OFDM). In practice, the antenna selection information is transmitted on a binary symmetry control channel with a crossing probability. The linear minimum mean square error (LMMSE) is the optimal technique for channel estimation in the MIMO-OFDM system. Although the LMMSE estimator works well with a low signal-to-noise ratio (SNR), in the presence of an antenna subcarrier allocation error (ATS), an irreducible error produces high SNR results.

Jacobsson *et al.* [6] has shown that the least squares channel (LS) associated with the common driver and the processing of the transmitted data represents the capacity obtained in the case of the single user single reception antenna.

3. OVERVIEW OF DEEP LEARNING

In machine learning, a small dataset is required to train the model whereas a large dataset is needed to train the deep learning model. Low-end machines are sufficient for machine learning processing since it requires less time for training but more computational time for testing. Whereas, in deep learning, high processing is required during the training process but very little time for testing. Therefore, deep learning is considered to be an emerging part of machine learning, consisting of diverse learning and representation learning. Since deep learning is a branch of machine learning that has proved its effectiveness over traditional machine learning models (shallow models) in most of the application areas, especially real life. Some of the differences between machine learning models and deep models are as follows:

- Run time: the run time of any learning algorithm is calculated for both training and testing time. Due to the complex structure of deep learning models, their training time is considerably more than shallow models, but the testing time is less.
- Parameters: during the training phase, two types of parameters are used: learnable parameters and hyperparameters. Before training starts, the hyperparameters are manually set, while during the training process learnable parameters are calculated automatically. In deep learning models, these parameters are large in number, so, it takes a longer time to optimize and train

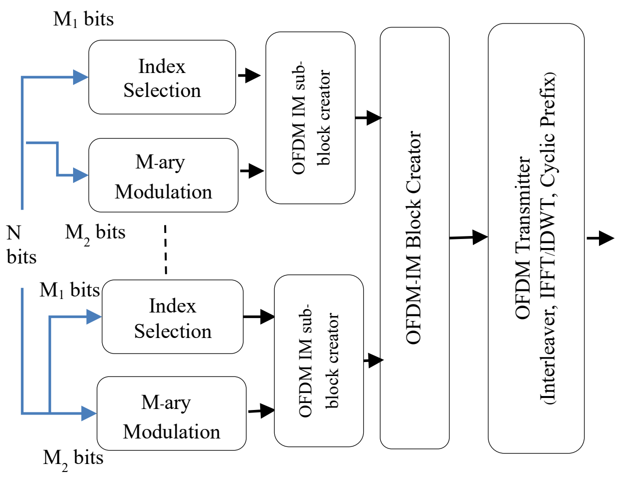

Fig. 1: *OFDM-IM transmitter.*

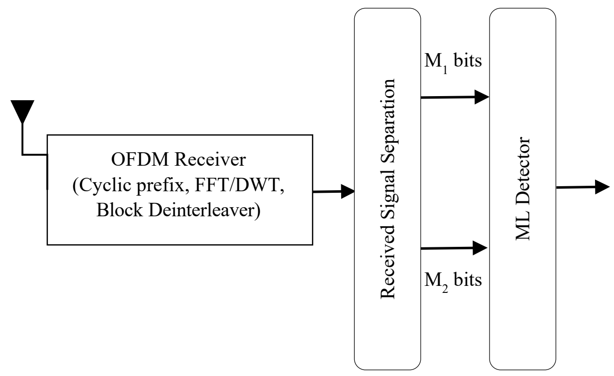

Fig. 2: *OFDM-IM receiver.*

the model.

- Learning capacity: due to the complex nature and large number of internal learning parameters, deep learning models have a better fitting ability compared to traditional methods. Due to a large volume set of data, traditional neural network models encounter an overfitting issue, while deep learning removes this problem and shows better performance.

Some of the popular deep learning architecture consists of deep brief networks (DBNs), deep neural networks (DNNs), or convolutional neural networks (CNNs), recurrent neural networks (RNNs), etc. This paper discusses the development of training-based channel estimation for a doubly selective faded noisy channel. Subsequently, joint channel estimation and equalization of a frequency indexed MIMO-OFDM system is proposed by intrinsically amalgamating them with a Viterbi decoder DNN framework. The algorithm will perform a comparison of the MSE performance and the proposed and existing schemes.

4. METHODOLOGY

With advancement of communication systems over the last few years, there have been advancements in speed of data transmission over channel. First-generation and second-generation data communication are known to be limited to only text and voice messages. In addition, third generation mobile and web application services have advanced over text data. Furthermore, fourth-generation communication systems have advanced through video data or live video conferencing with high data quality in 3D graphics. Similarly, advancement is also taking place in fifth- generation data and researchers are currently developing techniques under the 5G scenario. As with any advancement, an individual's lifestyle requires access to communication services anywhere at any time with fast data transmission speed [1].

With the rising demand for high-quality, fast data speed, the congestion or data traffic rate increases in the wireless environment. In order to fulfill such demand, many research works focus on reducing the hurdles in 4G or 5G communication channels. Broadband communication is termed as an idea that demonstrates the capability of the wireless channel [2]. Orthogonal frequency division multiplexing (OFDM) is a multicarrier modulation technique used to achieve a high data transmission rate with improved quality in noisy wireless channels and could be used for high-speed data transmission over indoor and outside wireless communication systems which divide the signal bandwidth into many subcarriers before transmitting data bits.

In such a multicarrier modulation technique, the available channel bandwidth is divided into many narrow subcarriers with specified frequency ranges, meaning that a small fraction of bandwidth is allotted to each sub-carrier. The overall throughput of the OFDM represents the combined throughput of each subcarrier. Therefore, the information rate of each subcarrier is also a fraction of the overall system. This OFDM feature supports a system design capable of supporting high data transmission rates while maintaining channel memory. The OFDM is a type of wireless channel application for reducing the multipath fading caused by obstacles in the path of transmission data that makes the system complex [3]. The idea of IM can refer to systems of communication other than those involving MIMO. For example, IM techniques can be implemented impressively as subcarriers of the OFDM system.

The OFDM-IM is the latest scheme in multi-vector transmission, proposed on the basis of the IM concept from SM (Figs. 1 and 2). The OFDM-IM diagram shows the distribution of the incoming bit stream into the M-bit constellation and the index selection only involves a subgroup of available subcarriers picked as active, while the remaining inactive subcarriers are set as zero and not used pursuant to the index selection bits. On the other hand, the modulation of active subcarriers is performed on the basis of M-ary constellation bits. Moreover, the transmission of information is not only conducted using data symbols like classic OFDM but also by active subcarrier indices to transmit the corresponding data symbols for OFDM. In the selection of an OFDM with

NF subcarriers, active subcarriers indices are preferable, such as the IM techniques used in the transmission of MA-SM system antennas. For each frame, a total of

$$m = pG = (\log_2 \tbinom{N}{K}) + K \log_2 M)G \quad (1)$$

transmitted bits are required, where $p = p1 + p2$ and $p2 = K \log_2 M$. G contains selected indices vector and symbols of M-ary with $K \times 1$ dimensions.

Primarily, the creator of OFDM-IM subblock uses the $N \times 1$ subblocks of OFDM-IM x_g where $g = 1, \dots, G$, then the creator of OFDM-IM block obtains the $NF \times 1$ main OFDM-IM frame x by combining these G subblocks of OFDM-IM. Furthermore, the $G \times N$ block can be interleaved to ensure the subcarriers of the subblock are dominated by uncorrelated fading wireless channels. Ultimately, classical OFDM procedures are applied such as cyclic prefix (CP), inverse fast insertion, digital-to-analog conversion (DAC), and Fourier transform (IFFT). The noise in the wireless channel is further estimated using the channel estimation technique. This is an essential technique mainly used in the wireless system. Due to the continuous mobility, the transmitter or receiver with respect to time changes in wireless communicating channels is affected by surroundings, i.e., buildings, poles, hills, vehicles, flats, congestion, etc. This results in a distorted transmitted signal being received, causing difficulties in the recovery of original data bits. For high precise transmission, channel estimation is required at the mobile receiver end for high quality of service (QoS) [7]. In this paper, frequency index modulation in OFDM-IM is investigated and the performance analyzed, as discussed in further sections.

4.1 System Models and Techniques

The number of information bits processed within each group is represented by b, while N represents the number of parallel groups into which the information bits have been divided; a b_N represents the number of information bits. Out of the X_n available indices, X active indices will be assigned by the index modulation selector. The K code words are then generated through the sub-inputs N_2 of the remaining m bits. For the improvement of BER and to enhance the diversity gain, the active indices are employed to map and inter-leave L code words. The series-to-parallel conversion takes place for the generated data and a single frame formed from it. The OFDM modulation is then performed and the data transmitted. For the system proposed in the present research, OFDM modulation along with N_c subcarriers is considered. The subcarriers have an equal division of N groups, with $M_g = N_c/N$ subcarriers existing within the frequency domain of each group. Within each subcarrier group, K represents the number of indices in an active state while N_a denotes the number of available subcarriers within the virtual domain. Very large values may be assumed by N_c and if it is directly related to the N_c, multiple combinations pertaining to the active indices exist. The selection of active indices is thus a hectic task and the subcarriers are therefore divided into smaller N groups. At the transmitter's input, the information bits are divided into G groups. The upcoming sections discuss the details pertaining to the transmitter and receiver models.

4.2 Transmitter Model

The bG data bits are divided into N groups with a length of b bits (Fig. 3). The IM selector and convolution STTC encoder are then utilized to process these b bits within each transmitter group. As far as the operational strategy method is concerned, the square codes are different in comparison to the convolution codes. At this stage, there is no complete information on the memory component quantity, quantity of bits input to the encoder, and output from it. Gone are the days when the encoder was just a black box and no information existed on the components utilized for the creation and extraction of bits. In order to understand the manner in which memory components are connected to the encoder, the so-called "generator polynomials" are utilized.

During transmission, bG data bits are split into N groups of length b bits and the corresponding b bits then processed in each group of the transmitter by the convolution STTC encoder and the IM selector. The time and frequency selective channel model is

$$h(t,\tau) = \sum_l \sum_\mu a_{l,\mu} \exp\left[j\left(\varphi_{l,\mu} + 2\pi f_{\max}\cos(\beta_{l,\mu}t)\right)\right]\delta(\tau - \tau_l) \quad (2)$$

where l is the index for multipath $\{0 \le l \le L\}$, $a_{l,\mu}$ is the path dependent amplitude, $\varphi_{l,\mu}$ is the arrival angle, $\beta_{l,\mu}$ is the phase, and τ_l is the time delay.

The discrete time channel after sampling is

$$h(n,l) \stackrel{\triangle}{=} h(nT_s : \tau) \quad (3)$$

where T_s is the sampling duration.

This paper focuses on noise estimation in the AWGN channel.

4.3 Channel Fading and Noise: Doubly Selective Fading

The propagation model of free-space provides a simple theoretical explanation for propagation loss, while transacting with satellite and other communication systems where the receiver and transmitter each have a line of sight. However, several obstructions can interlope in the signal transmission with ground communications. The signals can be diffracted and reflected by many surfaces (like densely wooded areas, buildings, rough terrain, and mountains) before arriving at their destination. These obstacles affect the division of signals and are the reason behind their delay or arrival at narrowly distinct times.

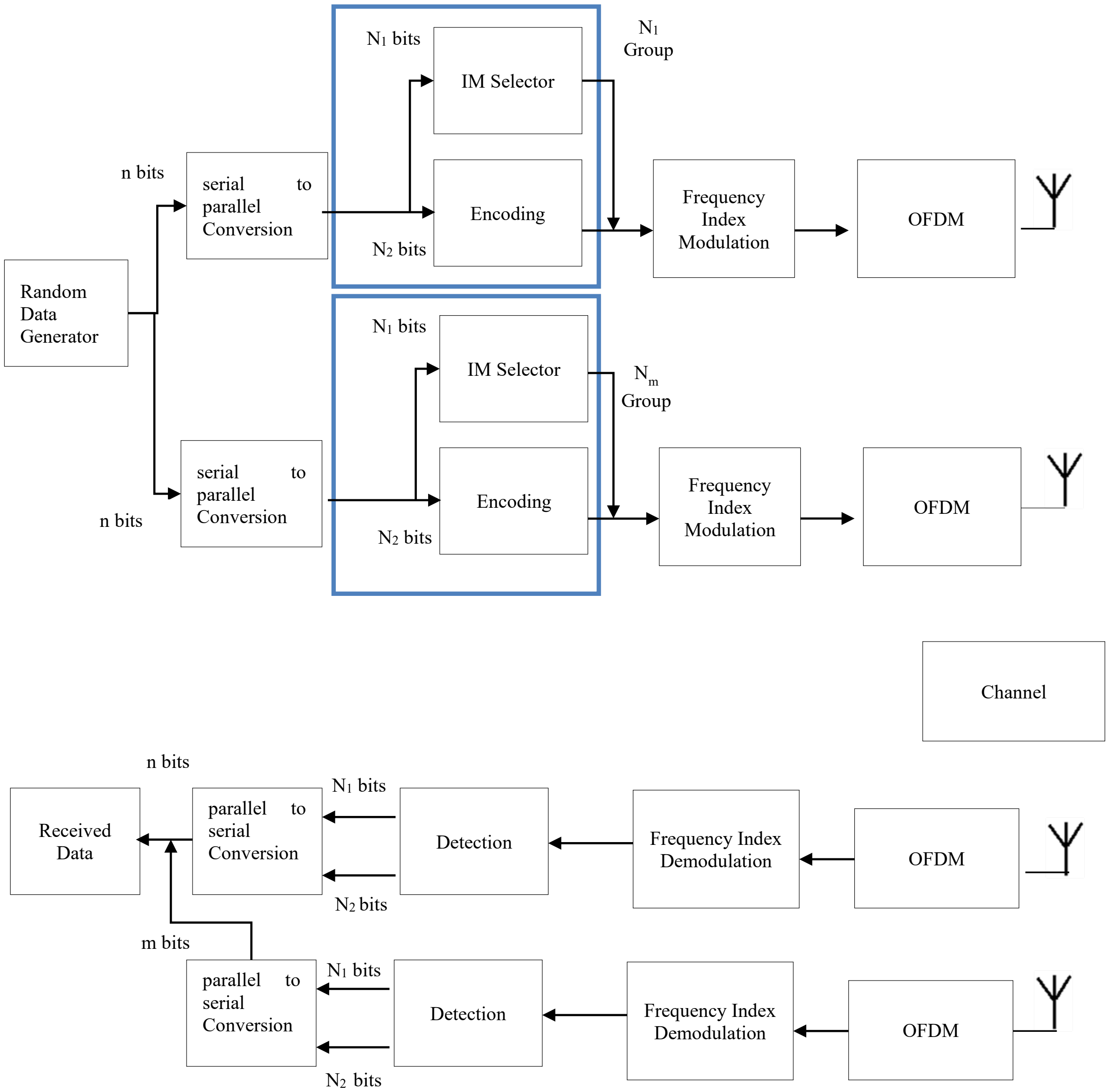

Fig. 3: *Transceiver architecture.*

This terminology is called multipath propagation and causes a real-world communication terminology known as fading.

In the communicating channel, noise is analyzed using some ideal noise values existing in real scenarios, termed as additive white Gaussian noise (AWGN). Such noisy channels generate noise that is independent of frequency and causes distortion to the transmitted signals.

In spite of this, AWGN is calculated on the basis of its spectral power density as:

$$S_w(f) = \frac{N_0}{2} \tag{4}$$

where N_0 is a constant value and the factor 1/2 is assumed, indicating that half the power spectral is associated with positive frequencies and the other half with negative frequencies. In AWGN, the amplitude of noise is distributed over the channel using the Gaussian function. Since AWGN is simple to implement and its mathematical model easy to understand.

4.4 Receiver Model

With proper utilization of the channel model at the n_c-th subcarrier existing between the n-th receiver antenna and the m-th transmitter antenna, and subsequent CP removal, Eq. (5) is achieved.

$$Y[n] = H[n] * S[n] + \text{noise}[n] \tag{5}$$

where $Y[n]$ is the received at n-th subcarrier, $H[n]$ is the channel matrix, $S[n]$ is the compressed bg transmitted prior to detection can thus be obtained, and noise$[n]$ is the channel noise.

The block splitter then absorbs the received signal $Y[n]$ and the specific detection of received signals within N groups is achieved. The $Y[n]$ signal is received within the

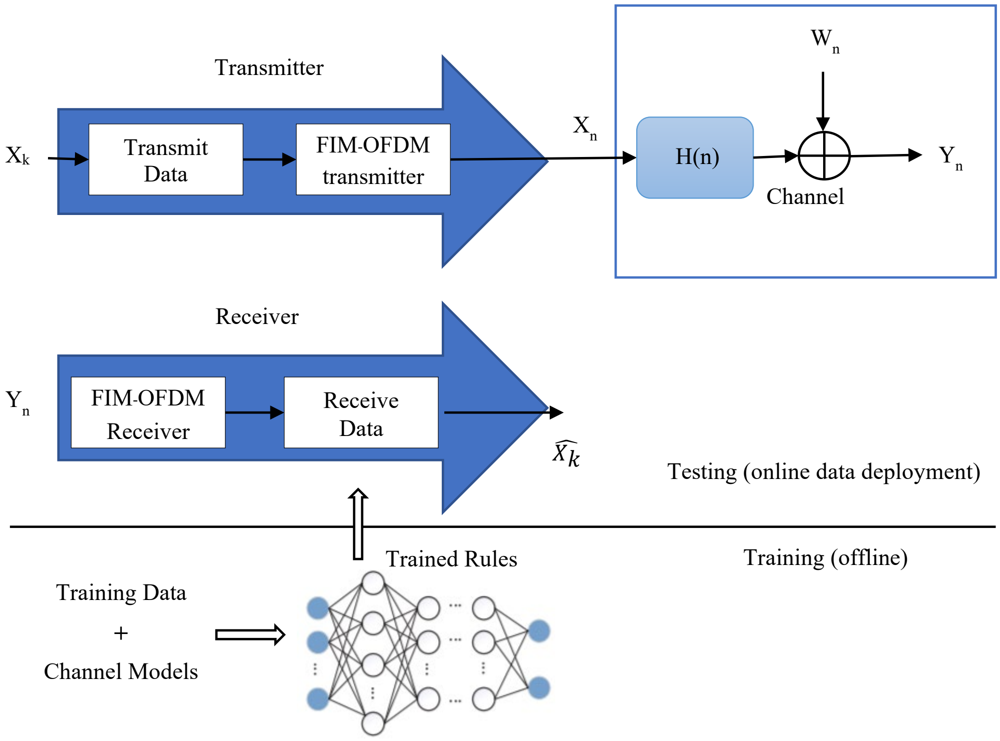

Fig. 4: *DNN based channel estimation.*

n-th group. An enhanced data rate within the spread of the time delay environment giving effective equalization is supported by OFDM. Channel state information (CSI) is required for equalization. The OFDM system receives the pilots within the predetermined subcarriers as training signals. The guard interval is employed to drop the inter-symbol interference within the channel estimation. The received signal is represented by

$$Y(k) = X(k)H(k) + W(k) \tag{6}$$

where $Y(k)$ is the received signal vector, $X(k)$ is the matrix composes the transmitted signaling points within the diagonal, and $H(k)$ is the channel attenuation vector.

4.5 Linear Minimum Mean Square Error (LMMSE) Channel Estimation

Linear minimum mean square error (LMMSE) is an optimal channel estimation technique with respect to the mean square error rate but is highly complex. This technique is used to track the time and frequency domain. Information on noise and channel statistics is required, being priori unknown at the receiver for LMMSE estimation. The LMMSE estimation is performed along the frequency domain and the minimum cost function estimated as:

$$J\,(\text{LMMSE}) = E\left\{\|H_n - DY_n\|^2\right\} \tag{7}$$

where D is the matrix whose coefficients must be optimized. H_n^{LMMSE} is the estimated channel frequency response vector

$$H_n^{\text{LMMSE}} = D_{opt}Y_n \tag{8}$$

where D_{opt} is the channel covariance matrix along the frequency axis, calculated as:

$$D_{opt} = R_H X_n^H \left(X_n R_H X_n^H + \sigma^2 I\right)^{-1} \tag{9}$$

where $I = M \times M$ identity matrix, $R_H = M \times M$ channel covariance matrix along the frequency axis, $(\cdot)^H$ is the Hermitian transpose, and σ^2 is the noise variance. Thus,

$$H_n^{\text{LMMSE}} = R_H X_n^H \left(X_n R_H X_n^H + \sigma^2 I\right)^{-1} H_n^{\text{LS}} \tag{10}$$

where H_n^{LS} is the channel frequency response vector with LS estimated samples.

4.6 Deep Neural Network-Based Channel Estimation

As presented in Fig. 4, the proposed DNN-based channel estimation algorithm has two stages: training and testing. The DNN-based channel estimator adopts the fully connected feedforward deep neural network with N layers and $N-2$ hidden layers. Hidden layers consist of "n" neurons. Each neuron represents the nonlinear transformation (rectified linear unit, ReLU) of a weighted summation in output values of the preceding layer [8–10]. The activation function is stated as

$$f\,(x) = \begin{cases} 0, & \text{for } x < 0 \\ x, & \text{for } x \geq 0 \end{cases} \tag{11}$$

Table 1: *System parameters used in simulation.*

Parameters	Values
Multicarrier system	OFDM
Number of subcarriers	128
Length of cyclic prefix	16
Number of subcarrier groups (N)	16
Number of available indices/groups	16
Number of active indices/groups	4
Channel specification	AWGN/Rayleigh fading
Signal-to-noise ratio (SNR)	0–20 dB

Firstly, the DNN is trained with simulated data. While in the testing stage, the channels can be dynamically tracked by the DNN with trained rules and the transmitted symbols then detected.

1. Training Phase:

During the training phase, the input and pilot symbols are known and considered to be input data for the DNN. The proposed DNN adopts the LMMSE estimator and trains the model accordingly. In each simulation, the data sequence is created randomly and considered to be the transmitted signal and forms corresponding FIM-MIMO-OFDM symbols with a sequence of pilot symbols. These pilot symbols are known to be at fixed positions during the training phase. These signals are then transmitted over random channel conditions, i.e., with fading or noise. The received signal based on FIM-MIMO-OFDM frames contains transmitted symbols along with channel noise. The received signal and the original transmitted data are collected as the training data. The model is then trained to minimize the difference between the output of the deep neural network and the transmitted data.

The loss function used here is

$$\text{Loss} = \frac{1}{N}\sum_{K=1}^{N}\left(\widehat{X_k}^2 - X^2\right) \tag{12}$$

where $\widehat{X_k}$ is the prediction data values, $X(k)$ is the supervision data values (transmitted signal).

2. Testing Phase:

During the testing phase, the received channel information symbol is fed into the DNN which has the same structure as in the training stage. The trained parameters are loaded and the input passed to predict the estimated channel. The ML detector is then used to estimate the information bits.

5. ANALYSIS RESULTS

In this paper, different experiments were conducted to analyze the performance of the deep neural network (DNN) with channel estimation under noisy and faded wireless communication systems. A DNN model was trained based on simulation data and compared with the traditional methods in terms of mean square error (MSE) under different signal-to-noise ratios (SNRs). The SNR is termed as the strength of the desired signal relative to channel noise. In the following experiments, the deep learning-based approach proved to be more robust than LMMSE. In the simulation, the proposed MSE performance was analyzed under a faded noisy channel using MATLAB software with the frequency index modulation technique. Table 1 shows the system parameters used in the simulation.

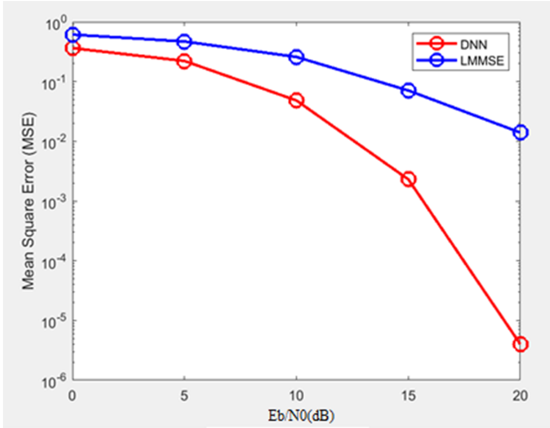

Fig. 5: *MSE analysis for DNN and LMMSE based channel estimation without CP.*

The methodology is simulated and compared with the variable signal-to-noise ratio (E_b/N_0) as shown below. The mean square error (MSE) performance of these schemes is evaluated using Monte Carlo simulation. The MSE is the average square of the error of the received bits compared to the transmitted bits. The error is calculated as the difference between actual values and estimated values as

$$\text{MSE} = \frac{|E_v - A_v|^2}{N} \tag{13}$$

where E_v is the estimated value, A_v is the actual value, and N is the number of bits.

Fig. 5 shows the MSE analysis of the DNN and LMMSE channel estimator without cyclic prefix (CP). The results demonstrate the effectiveness of DNN estimator over the LMMSE estimator.

Fig. 6 shows the MSE analysis of the DNN and LMMSE channel estimator with cyclic prefix (CP). The results demonstrate the effectiveness of DNN over the LMMSE estimator.

Fig. 7 shows the MSE analysis of DNN with and without cyclic prefix for FIM-MIMO-OFDM. The results demonstrate the effectiveness of the CP DNN estimator over the model without CP DNN.

Table 2 presents the time complexity analysis of both DNN and LMMSE channel estimation. It can be concluded that the proposed model is less complex in comparison to the conventional LMMSE algorithm.

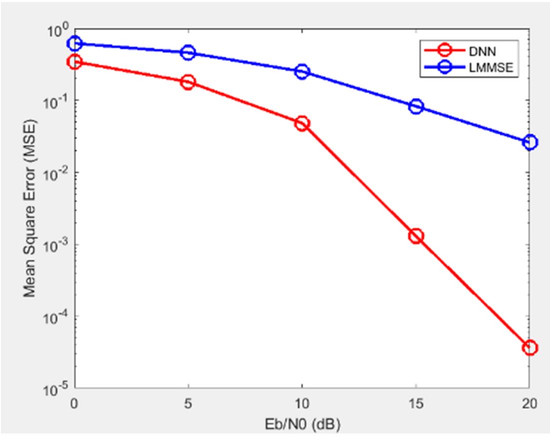

Fig. 6: *MSE analysis for DNN and LMMSE based channel estimation with CP.*

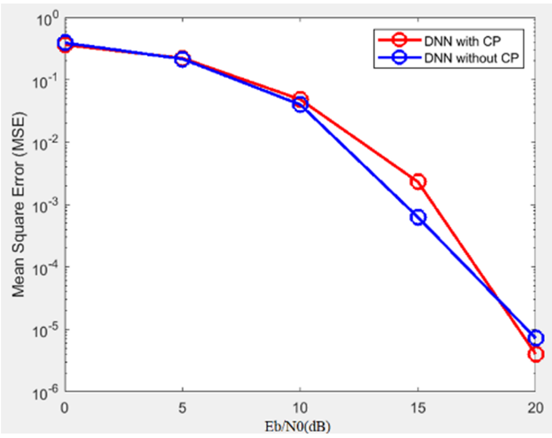

Fig. 7: *MSE analysis for DNN with and without CP.*

6. CONCLUSION

The modulation index is an emerging term, whereby additional bits of information are paired to the indices of resources in various transmission conditions such as slots or subcarriers and antenna indices. In this paper, the OFDM with IM (OFDM-IM) is revealed to be a more beneficial frequency-domain IM technique in comparison to classical OFDM. The DNN based channel estimation algorithm for faded noisy channels proposed in this paper is trained on simulated data. The DNN has certain advantages over conventional channel estimation techniques under distortion, fading, and interference. Under any situation, the DNN has the capability to analyze and estimate the channel state. In this paper, simulation is performed with and without cyclic prefix conditions. The analysis results demonstrate the supremacy of DNN over conventional estimators.

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Table 2: *Time complexity analysis.*

SNR	DNN	LMMSE
0 dB	0.119103	1.035594
5 dB	0.042211	1.065271
10 dB	0.038047	1.162208
15 dB	0.041577	1.179518
20 dB	0.037235	1.224087

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