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OFDM Networks for Enhanced BER And PAPR Mitigation in 5G Systems

[1]Komal Marotrao Chavhan, [2]Prof. Dr. Ravindra M. Deshmukh

[1,2]Department of Electronics & Telecommunication Engineering, DRGIT& R, Amravati, Maharashtra, India

[1]komalchavhan@gmail.com, [2]Deshmukhrm577@gmail.com

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ABSTRACT

O-OFDMNet, an intensity-modulated direct detection transmission system, employs deep learning-aided optical orthogonal frequency division multiplexing (O-OFDM). O-OFDMNet utilizes deep neural networks (DNNs) to convert a complex-valued signal at the transmitter into a non-negative signal in the time domain and vice versa at the receiver. Unlike traditional radio frequency (RF) OFDM, O-OFDMNet retains the related frequency-domain signal processing. Unlike current O-OFDM schemes which rely on the Hermitian symmetry of the spectral-domain signal to ensure the real-valuedness of the time-domain signal, our approach achieves equivalent spectral efficiency to the RF scheme, a milestone previously unattained by any existing methods. As an autoencoder architecture, the example shows that O-OFDMNet may be taught in an end-to-end manner to simultaneously improve the bit errors ratios and the transmission's peak-to-average ratio of power. across frequency-selective channels and additive white Gaussian noise environments. Additionally, technique achieves throughput comparable to RF-OFDM, significantly surpassing that of traditional O-OFDM.

1. INTRODUCTION

The primary objective of wireless communication technology is to facilitate high-speed data transmission for ubiquitous personal and multimedia communication, irrespective of location or mobility. However, the wireless channel introduces several distortions into the transmitted signal, including inter symbol interference (ISI), multipath fading, and additive noise. As fifth-generation (5G) mobile cellular technology predominantly operates as a Multiple Input Multiple Output (MIMO) system, comprising numerous Single Input Single Output (SISO) channels connecting various antennas, its key objectives include supporting higher data rates and delivering seamless services across diverse wireless devices and networks. Consequently, it is plausible to consider leveraging multiple SISO channel estimations as a foundation for MIMO channel estimation. It is expected that the complexity of Deep Learning-based Channel Estimation (CE) in Multiple Input Multiple Output (MIMO) systems will escalate exponentially with the number of antennas. This will lead to a significant increase in complexity during both the online and offline phases, necessitating the adoption of suboptimal techniques for MIMO CE estimation based on Single Input Single Output (SISO) calculations. While the primary focus of this paper is on SISO channel estimation, our future research endeavors aim to encompass MIMO channel estimation while considering complexity constraints. Orthogonal Frequency Division Multiplexing (OFDM) stands out as a novel strategy employed by 5G to mitigate inter symbol interference (ISI) and fading in multipath scenarios [1].

OFDM is renowned for its high spectrum efficiency and inherent resilience to multipath fading and inter symbol interference (ISI). By adjusting the transmitted power and/or modulation order independently for each sub-band according to its noise background and channel response, OFDM enables the attainment of high data rates. However, precise Channel Estimation (CE) procedures are essential both before and during data transmission to ensure accurate bit loading and power adjustment for each sub-band. One widely used CE technique is Pilot-Aided Channel Estimation (PACE), which entails modulating a predetermined subset of OFDM carriers (pilots) using a known training sequence. The received pilots are then analyzed to estimate channel characteristics. The two most commonly utilized standard Channel Estimation (CE) techniques are Least Squares (LS) and Minimum Mean Square Error (MMSE) [2]. Recently, Deep Learning (DL) has garnered significant attention in communication systems [3-5]. Various approaches in DL-based communication systems have been proposed to enhance the performance of traditional algorithms. These encompass modulation recognition [6], signal detection [7], channel equalization [8], Channel State Information (CSI) feedback [9], and CE [10, 11].

2. RELATED LITERATURE

In the literature, numerous studies have explored channel estimation techniques in Orthogonal Frequency Division Multiplexing (OFDM) systems. Estimators for Least Squares (LS) and Minimum Mean Square Error (MMSE) are discussed in [6]. The authors of [7] introduce an MMSE channel estimator that fully exploits the frequency response of time-varying dispersive fading channels, considering both temporal and frequency-domain correlations. When considering noise, the MMSE method demonstrates superior performance over LS in terms of Mean Square Error (MSE). However, this approach requires knowledge of specific parameters of the channel model and entails additional processing power. Conversely, LS is a simpler and more straightforward algorithm to implement.

Some research aims to simplify MMSE-based channel estimation methods. For instance, a new low-rank Linear Minimum Mean Square Error (LMMSE) approach to reduce the complexity of the filtering matrix is proposed in [9], while [8] presents a simplified Linear Minimum Mean Square Error (LMMSE) channel estimation algorithm leveraging Fourier Transform methodology and aided by suitable training sequences.

The significant potential of Massive MIMO (MaMIMO) technology has spurred extensive research in channel estimation within these systems over the past two decades. In [10], the performance of a Multiple-Input-Multiple-Output (MIMO)-OFDM system trained using linear interpolation on data subcarriers and Least Squares (LS) estimation on pilot subcarriers is evaluated. For the space-time block-coded spatial modulation systems, spline interpolation and pilot symbol-based channel estimation have been presented in [11] to monitor the channel fluctuations in the presence of Rician fading channels.

The results of the simulations demonstrate that the closest neighbor and piecewise linear interpolation are not as effective as the suggested spline interpolation. A methodology for MMSE-based channel estimate is presented in [12] for MaMIMO systems in an effort to lower the overhead associated with downlink channel training in FDD settings. In order to reduce overhead, just a selection of antennas is trained, and the CSI at the antennas that remained silent throughout the pilot transmission time is computed using MMSE interpolation, which makes use of the spatial correlation.

Moreover, in [13], the authors propose a channel interpolation approach that partitions the Uniform Rectangular Array (URA) into smaller URAs, enabling MMSE interpolation with minimal computational cost within each URA. Reference [14] introduces a pilot sequence design aimed at minimizing errors in MMSE channel estimation. When systems encounter pilot contamination, alternative works offer estimation techniques that either reduce the computational burden of conventional estimators or enhance system performance [15], [16]. Earlier references endeavor to minimize estimation errors and computational overhead in MIMO systems by either modifying conventional channel estimators or refining parts of the estimation process. Recent research focuses on employing deep learning techniques in both data-link layer and physical layer communications. This trend is driven by two primary factors [17].

Firstly, while traditional signal processing algorithms, relying on mathematical models can only approximate the intricacies of real-world communication networks, deep learning-based methods have the capability to optimize them effectively.

Secondly, deep learning algorithms are structured in layers that perform fundamental functions. The advancement of massively parallel computing architectures, such as Graphics Processing Units (GPUs) and specialized circuits, facilitates remarkable computational throughput and energy efficiency [18], [19].

Deep Neural Networks (DNNs) are highly efficient due to their significant parallel processing capabilities. Various aspects of communication systems have benefited from the application of deep learning techniques, including MIMO signal recognition [20], error-correcting codes [21], and channel resource allocation [22].

Moreover, numerous studies have demonstrated the effectiveness of deep learning in channel estimation. Some researchers have employed Convolutional Neural Network (CNN) architectures to emulate the successful outcomes of image processing in addressing the channel estimation challenge. For instance, in [23], CNN is utilized to estimate the channel response by modeling the time-frequency channel response as a 2D image. Similarly, in [24], intricate CNN architectures leverage characteristics of the modified angle-delay domain and the spatial-frequency domain for channel estimation.

In [25], the authors explore the efficacy of various 2D-CNN designs and 3D-CNN architectures, leveraging the spatial correlation inherent in the MIMO-OFDM channel. Additionally, a recurrent neural network (RNN) is developed to further exploit temporal domain correlation [25].

However, the primary focus of this study lies on channel estimation using Deep Neural Networks (DNNs). In [26], DNNs are employed for signal detection and channel estimation in OFDM systems. The wireless channels and OFDM modulation are treated as "black boxes" by the models. Consequently, the proposed deep learning-based method indirectly estimates Channel State Information (CSI).

For applications requiring the entire channel response, the approach mentioned above may not adequately discern the time-frequency channel response. In [27], the authors propose a deep learning-based DNN channel estimation method tailored for doubly selective OFDM channels (both frequency and time). The proposed system consists of three main components:

1. Pre-training, where weights are initialized.
2. Training, aimed at instructing the channel estimation technique.
3. Testing, and evaluating the DNN's performance on unseen data.

The authors feed various inputs to the DNN, including transmitted pilot symbols during both training and testing stages, as well as information symbols during pre-training, alongside the LS-based pilot estimate.

3. PROPOSED LSTM NEURAL NETWORK

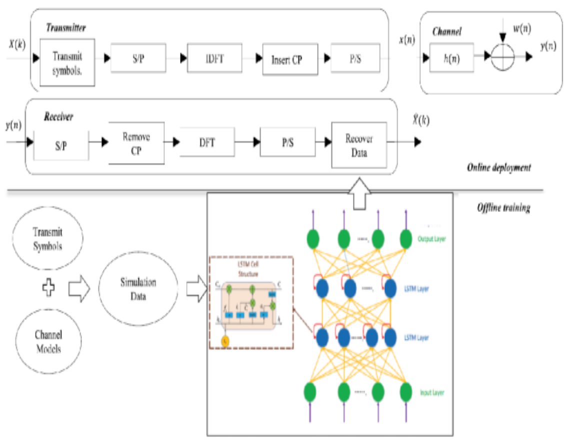

Figure 1. System model of DL-based channel estimation

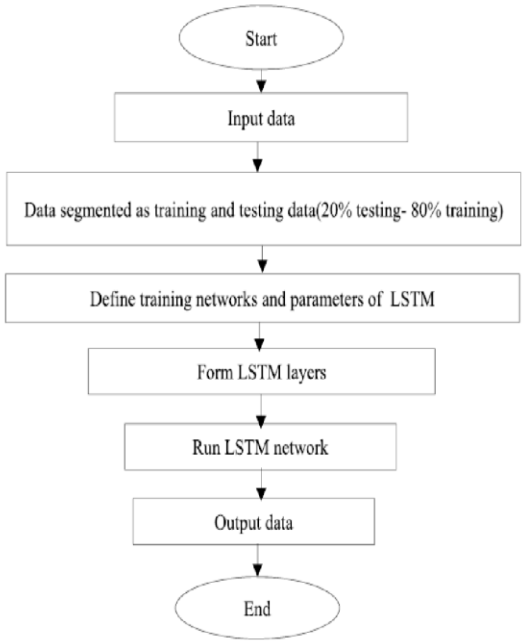

Figure 2. The flow chart of the proposed LSTM neural network

Model Training: The model is trained under the assumption that wireless channels contain hidden data and that OFDM modulation is utilized. In recent years, researchers have developed several channel models that leverage channel data to characterize the channel. The received OFDM signal is acquired amidst noise and channel distortion within an OFDM frame. Training data is compiled from both the original signal and the received signal.

For the DL model input, a pilot block and a data block are provided. To construct what the term a "Feature vector" for both the training and testing stages, the real and imaginary components of a complex input vector are extracted. Subsequently, these values are combined to form a double-size real-data vector, as depicted in Figure 8 [2].

During the training phase, these feature vectors are fed into the Long Short-Term Memory (LSTM) model in batches, along with the corresponding target symbols. The LSTM model is trained to predict the matching symbol for each extracted input feature vector during both testing and prediction stages.

The training process aims to minimize the disparity between the original message and the output generated by the neural network. This optimization ensures that the model learns to accurately predict the symbols based on the input feature vectors.

The L2 loss function is indicated below.

$Y(k) = X(k) \cdot H(k) + W(k)$

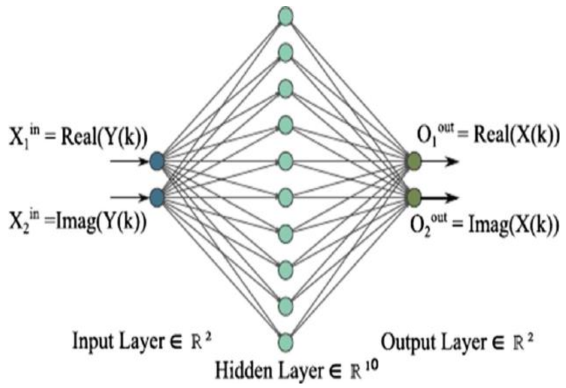

Figure 3. The proposed deep neural network for estimating complex input vector

4. Simulation Results

The performance of DL approaches for combined Channel Estimation (CE) and symbol identification in OFDM wireless communication systems is elucidated through three MATLAB script files.

The first script demonstrates the process of generating training and validation data for the DL model within a single-user OFDM system. Validation and training data are collected for a single subcarrier, focusing on specific parameters. Each transmitted OFDM packet contains one data symbol and one pilot symbol. The pilot sequence may include a mixture of data symbols.

Each training sample is represented by a feature vector structured similarly to the sequence classification MATLAB example using an LSTM network. It encompasses every symbol received in an OFDM packet.

The second script configures the training settings for the DNN. It utilizes the training data for a specified subcarrier to train the DNN model.

The third script is responsible for conducting model testing. It generates testing data and evaluates the Bit Error Rate (BER) using DL, LS, and MMSE methods for each signal-to-noise ratio (SNR) point.

System parameters

The simulation was carried out under the OFDM system settings. Perfect synchronization was assumed, and a guard interval larger than the maximum delay spread was selected to mitigate Intersymbol Interference (ISI).

Various channel models and signal-to-noise ratios (SNRs) were employed in the simulations. In our setup, SNR represents the Energy per Symbol per Noise Power Spectral Density (Es/No).

Channel model

To design and evaluate a wireless communication system effectively, a thorough understanding of the channel model is crucial. Currently, two-channel models are under consideration for link-level evaluations in 5G:

Clustered Delay: This model represents the wireless channel as consisting of clusters of paths, where each cluster represents a group of paths with similar delay characteristics. This model is particularly useful for simulating environments with rich multipath propagation, such as urban or indoor scenarios.

Tapped Delay Line (TDL): The TDL model represents the wireless channel as a sum of delayed and attenuated versions of the transmitted signal, known as taps. Each tap represents a distinct propagation path, characterized by its delay and attenuation. This model is widely used for simulating various channel conditions, including Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) scenarios.

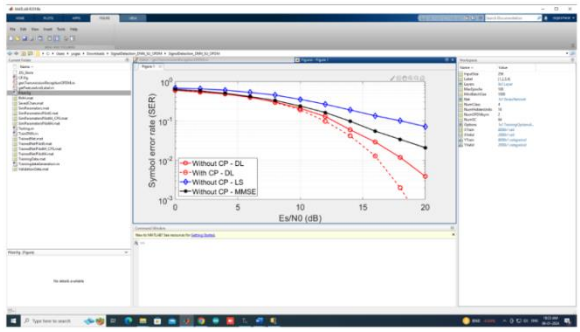

Figure 4. Simulation Result When Using TDL Channel Model

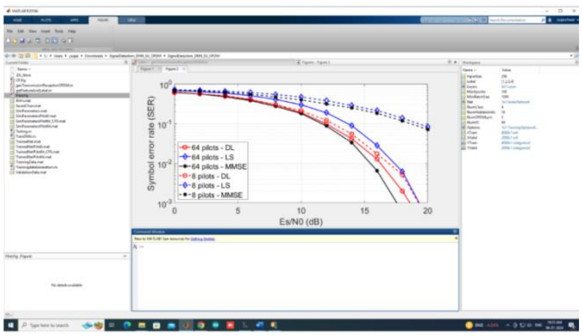

Figure 5. Simulation Result When Using 3GPP TR38.901 Channel Model

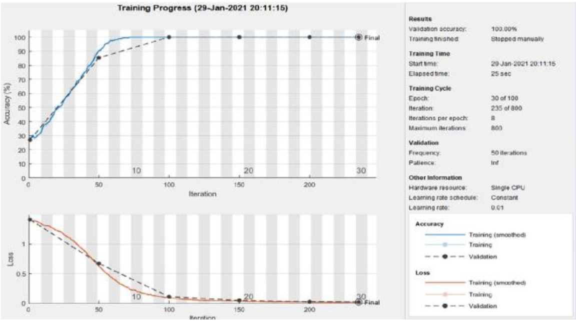

Figure 6. The LSTM network model training

CONCLUSION

In the initial phase of the project, considerable effort was dedicated to researching and gathering bibliographical material to identify prior work as a starting point and to pinpoint potential applications. Two distinct case studies, namely the channel estimation and feedback reporting modules, were selected based on this early investigation.

Instead of relying on conventional algorithms, specific deep neural networks were developed and integrated into the New Radio link simulator, which was created in the laboratories of Telecom Italia. These deep-learning solutions were implemented to enhance the performance of both the channel estimation and feedback reporting modules within the simulator's physical blocks.

In the final stage of the project, after completing the implementation work, a simulation and performance assessment phase was initiated. However, the data obtained did not support the assertion that significant gains would arise from integrating deep learning methods into the physical transmission chain of 5G systems.

While conventional algorithms may leverage mathematical models to simplify and approximate reality, deep learning solutions have the potential to outperform these regular algorithms, especially in scenarios where mathematical models may not fully capture the complexities of real-world environments.

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