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Research article

LSTM projected layer neural network-based signal estimation and channel state estimator for OFDM wireless communication systems

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Abstract: Advanced wireless communication technologies, such as 5G, are faced with significant challenges in accurately estimating the transmitted signal and characterizing the channel. One of the major obstacles is the interference caused by the delay spread, which results from receiving multiple signal copies through different paths. To mitigate this issue, the orthogonal frequency division modulation (OFDM) technique is often employed. Efficient signal detection and optimal channel estimation are crucial for enhancing the performance of multi-carrier wireless communication systems. To this end, this paper proposes a Long Short Term Memory-Projected Layer (LSTM-PL) deep neural network(DNN) based channel estimator to detect received OFDM signal. The results show that the LSTM-PL algorithm outperforms traditional methods such as Least Squares(LS), Minimum Mean Square Error (MMSE) and other LSTM deep learning channel estimation methods like Long Short Term Memory(LSTM)-DNN and Bidirectional-LSTM(Bi-LSTM)-DNN, as evidenced by Symbol-Error Rate (SER) outcomes.

Keywords: OFDM; deep learning; channel estimation; LSTM; LSTM-PL

1. Introduction

In modern wireless communication systems, accurate estimation of wireless channels is essential for detecting transmitted signals, decoding them optimally, and recovering data. The OFDM technique is widely used in 5G wireless communication systems to combat the effects of multi-path fading and interference [1, 2]. OFDM is a digital modulation technique that divides a wide-band channel into multiple narrow-band sub-channels, each of which is modulated with a different carrier frequency. This helps to mitigate the effects of multi-path fading, which can cause a signal to experience multiple reflections and arrivals at the receiver, leading to distortion and fading [3]. The estimation of wireless channels is typically performed using conventional techniques such as LS and MMSE methods [2, 3]. However, the performance of these methods can be limited by non-linearities and imperfections in the system. To address these issues, DNNs have been increasingly used to model wireless channel characteristics [4]. By leveraging the power of machine learning, DNNs can learn the complex mapping between transmitted signals and received signals, and provide more accurate and robust channel estimation. With the growing popularity of DNN-based techniques, they are expected to play a crucial role in the development of advanced wireless communication systems, including 5G and beyond [5–7].

Mohammed A.S.M et al [8] have shown that DNNs with LSTM layers can outperform conventional channel estimation methods in OFDM systems with different channel models. D Venkata Ratnam et al [9] compared the performance of DNNs with LSTM and Bidirectional LSTM (Bi-LSTM) layers, as well as conventional channel estimation methods, in OFDM systems. Their results showed that the Bi-LSTM based DNN estimator outperformed both the LSTM DNN and the conventional methods in terms of accuracy and robustness. To further improve the performance of OFDM systems, advanced neural network techniques have been proposed, such as the LSTM Projected Layer (LSTM-PL). The LSTM-PL is a recurrent neural network(RNN) that is well-suited for predicting and estimating time-series data, making it an excellent candidate for wireless channel estimation [10]. The LSTM-PL model includes a projection layer that feeds into an LSTM layer, enabling more efficient processing of sequential data. The model can be trained using a vast data set of channel response samples to predict channel responses based on received signals.

Unlike traditional channel estimation methods like LS and MMSE methods, the LSTM-PL model doesn't need statistical information about the channel and can handle imperfections and non-linearities more effectively. Simulations evaluate the performance of the LSTM-PL model for wireless channel estimation, and the results shows that the proposed method outperforms the traditional LS, MMSE, LSTM methods in terms of SER performance. The LSTM-PL model has also been tested in various multipath scenarios, demonstrating its ability to estimate the wireless channel effectively under different channel conditions.

2. LSTM-PL based signal detection in OFDM systems

2.1. LSTM projected layer DNN

The LSTM-PL's unique architecture and memory mechanisms allow it to effectively learn from past data, capture dependencies between sequences, and accurately predict future outcomes. LSTMs have become popular in the field of deep learning because they are capable of assimilating information and long-term retention of data. In addition, LSTMs have been shown to be highly effective at tasks that involve processing sequences of variable length, due to their ability to adaptively adjust the memory cells in response to the specific characteristics of the input data [11].

The LSTM layer structure and cell state equations are given in [11]. Figure 1 shows the block diagram view of an LSTM projected Layer. In an LSTM projected layer, the memory cells are projected onto an output space through a linear transformation, which allows the network to produce a more interpretable representation of the stored information [12]. This projected representation can then be used to make predictions or decisions based on the input sequence. The projection layer also enables the network to be more easily fine-tuned for specific tasks, as the weights in the projection layer can be adjusted to optimize performance.

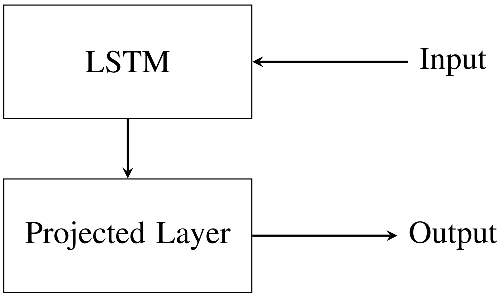

Figure 1. LSTM network with projected layer.

LSTM-PL offers several advantages over traditional LSTMs in certain applications. By projecting the memory cells onto an output space through a linear transformation, LSTM projected layers produce a more interpretable representation of the stored information, which can be useful in applications where it is important to understand the reasoning behind the predictions made by the network. Additionally, the projection layer in LSTM-PL can be fine-tuned to optimize performance on specific tasks, making them more flexible and adaptable to different applications [10].

The sizes of the learnable parameters of the layers that come after the projected layer are the same as those in the network that does not have the LSTM projected layer. When an LSTM layer is projected, it reduces the number of learnable parameters instead of reducing the number of hidden units, thus keeping the output size of the layer and downstream layers the same. This approach can lead to better prediction accuracy as it helps the network learn a more compact and expressive representation of the input sequence. In many LSTM-PL have been found to outperform traditional LSTMs due to the projection layer's ability to extract more relevant information from the stored memory. Furthermore, LSTM-PL can be more computationally efficient than traditional LSTMs, as they do not require separate computation for the gating mechanisms [10, 12].

2.2. System model

The OFDM system with transmitter, receiver and LSTM-PL DNN network shown in Figure 2. This system operates in a similar fashion to conventional OFDM systems. To initiate transmission, symbols with pilots are converted into a parallel data stream on the transmitter side. The stream is then transformed from the frequency domain to the time domain via an inverse discrete Fourier transform (IDFT). To address inter-symbol interference (ISI), a cyclic prefix (CP) is appended, with a length that is at least equal to the maximum delay spread of the channel [13].

Let a sample-spaced multi-path channel be denoted by complex random variables with N taps as $\{h(n)\}_0^{N-1}$, where each tap represents a different propagation delay, attenuation, and phase shift associated with the individual paths within the channel. Then the received OFDM signal can be represented as,

$$y(n) = x(n) \odot h(n) + w(n) \tag{2.1}$$

where $x(n)$ is the transmitted signal, $w(n)$ Additive White Gaussian Noise(AWGN) and $\odot$ represents circular convolution. After removing the CP and performing DFT, the received frequency domain signal is

$$Y(k) = X(k)H(k) + W(k) \tag{2.2}$$

where $Y(k)$, $X(k)$,$H(k)$ and $W(k)$ are the DFT of $y(n)$,$x(n)$,$h(n)$ and $w(n)$ respectively [4].

The first OFDM block of a frame is used for pilot symbols while subsequent blocks are used for data transmission. This allows the channel to be considered constant over both blocks but changing between frames. A two-stage process is used to develop a reliable LSTM-PL DNN model for joint channel estimation and symbol detection. The model is trained during the offline stage using diverse information sequences and various channel conditions, including urban or hilly terrain delay profiles with specific statistical properties. The effectiveness of the LSTM-PL model was assessed for signal detection and channel estimation in OFDM wireless communication systems.

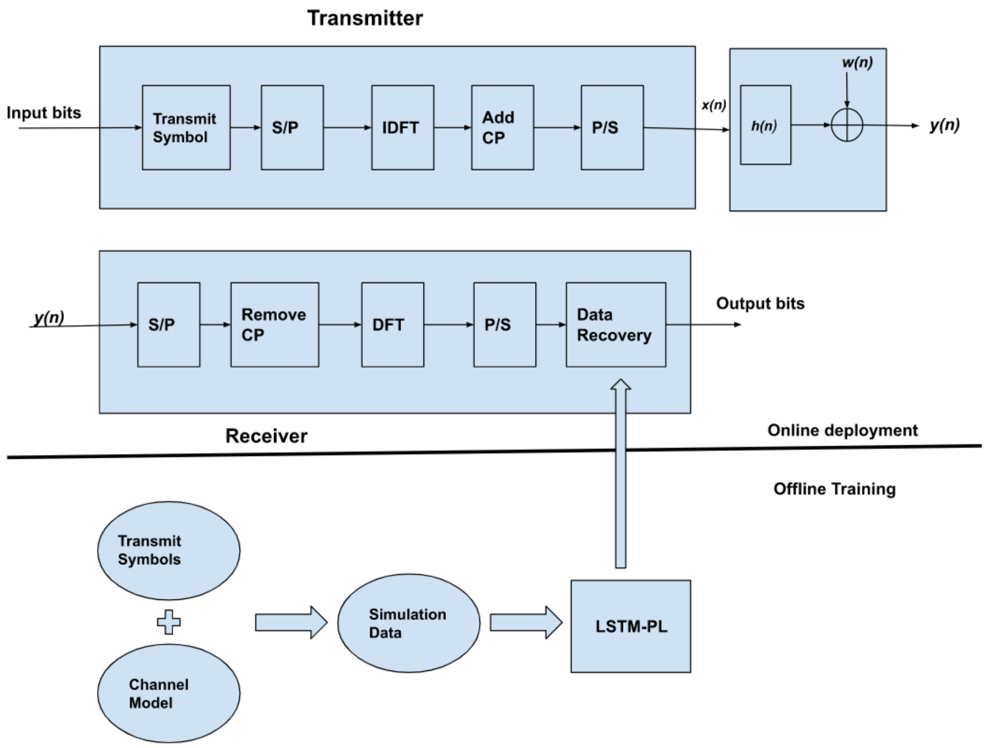

Figure 2. OFDM architecture with LSTM-PL DNN model.

The proposed DNN model comprises an input layer, three hidden layers, and an output layer. The input layer contains 256 nodes, and its size is determined by the sum of the real and imaginary parts of two OFDM blocks. Each block includes pilots and transmitted symbols used for channel estimation. The hidden layers are designed to learn the complex temporal dynamics of the wireless channel, while the output layer has four nodes that correspond to the predicted symbols, which correspond to the transmitted symbols. During online deployment, the LSTM-PL DNN model can recover transmitted data without requiring explicit estimation of the wireless channel. This is possible because the DNN can adapt to channel characteristics through training on a large datasets, enabling it to operate in real-time without complex channel estimation algorithms.

2.3. DNN model training

The DNN model is trained by utilizing simulation data generated from diverse channel models to effectively learn the channel characteristics [14]. In the proposed LSTM-PL model, the narrow band Rayleigh fading channel model [15–17] is employed for simulation. This model comprises of five layers, as shown in Figure 3, starting with the sequence input layer that has an input size of 256. The subsequent layer is the LSTM-PL with fewer input and output projected size. Following that, the four classes are formed through the utilization of a fully connected layer, a softmax layer, and finally, a classification layer which holds an output size of four. The model is trained to minimize the loss function, which serves as the key objective of the training process. In the proposed model, crossentropyex [8] is implemented as the loss function, facilitating the efficient calculation and reduction of the difference between the predicted and actual outputs. The model is trained to minimize the cost function using Adam optimizer and iteration is carried out till the error difference is within the threshold limit or very less.

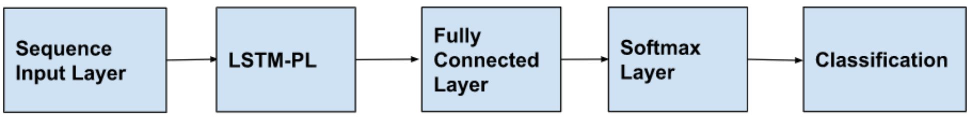

Figure 3. LSTM-PL DNN model.

3. Results

The potency of the DL LSTM-PL DNN-based channel state estimator is demonstrated in this section. To do this, the LSTM-PL DNN was offline trained on simulated datasets. The conventional as well as DNN-based estimators were compared with the proposed estimator SER at various SNRs. The training options and parameters for the LSTM-PL-based channel estimator can be seen in Table 1, while Table 2 contains the simulation parameters for the OFDM systems.

Table 1. Training parameters for the LSTM-PL DNN.

Simulation Parameters	Value
Input data size	256
Hidden Layers	16
LSTM-PL Output projected size	0.25× Hidden Layer
Optimization Techniques	Adam
Loss Function	crossentropyex
State activation function	tanh
Gate activation function	sigmoid
Mini-Batch size	1000
Maximum epochs	100
Momentum	0.9

During training, the LSTM-PL DNN is fed with the received signal, which consists of the OFDM pilots and transmission symbols, and the DNN outputs the corresponding symbol type of the transmitted signal. The pilot sequence was interleaved with a portion of the data symbols, and 10,000 OFDM packets were created. From these packets, 80 percentage were utilized for training, and remaining 20 percentage were utilized for validation and testing. The difference between the estimated and actual channel response is then computed using loss function, and the DNN parameters are updated using back propagation to minimize this loss.

By training the LSTM-PL DNN using received symbols comprising OFDM pilots and data symbols, the DNN can effectively learn the channel characteristics associated with the given pilot, capturing the intricate temporal dynamics of the channel response over time. Once trained, the DNN can be utilized to detect symbols in real-time for new input data.

Table 2. Simulation parameters for OFDM system.

Parameter	Value
Type of Modulation	4-ary Phase Shift Keying(QPSK)
OFDM Center Frequency	2.6 GHz
Channel Taps	24
CP	18
Number of OFDM sub-carries	64
FFT size	64
Pilots	8 and 4

The performance of the proposed estimator was assessed by training it with the Adam optimization technique under different pilot conditions 8 pilots and 4 pilots. To determine their effectiveness, the proposed estimator was compared in terms of SER with conventional LS, MMSE, and DNN-based estimators like LSTM-DNN and Bi-LSTN DNN estimators. These estimators were tested under identical channel conditions using a fewer number of pilots 8 and 4.

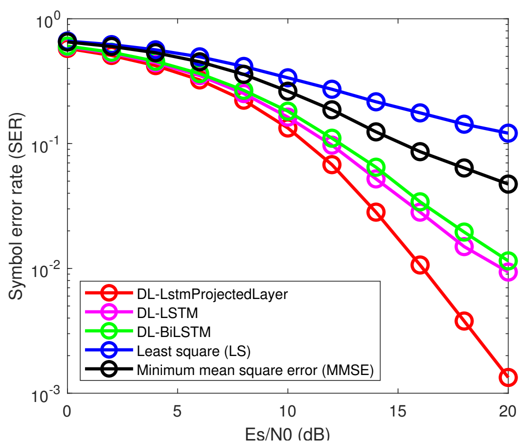

Figure 4. SER performance comparison when 8 pilots are used.

Based on the experimental results, it can be observed that the proposed LSTM-PL DNN estimator outperforms all other estimators across SNRs ranging from 0 to 20 dB when number of pilots is 8, as depicted in Figure 4. Figure 4 illustrates that the conventional LS and MMSE estimators, as well as DNN-based estimators like LSTM-DNN and Bi-LSTM DNN, become less effective at low SNR levels when only eight pilots are used. Conversely, the LSTM-PL estimator can improve the SER as the SNR increases.

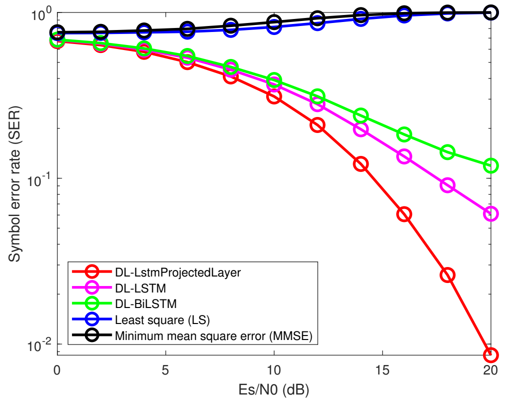

Figure 5. SER performance comparison when 4 pilots are used.

Figure 5 shows the SER performance when only 4 pilots are used. Here, both conventional estimators LS and MMSE lose their estimating power because as SNR increases, SER increases. There is no improvement of SER as SNR increases. However, DNN-based estimators perform much better than conventional LS and MMSE estimators. Additionally, it can be observed that out of all DNN-based estimators, LSTM-PL DNN performs much better than LSTM-DNN and Bi-LSTM-DNN.

Table 3. Learnable Parameters of DNNs

DNN	Total Learnable parameters
LSTM-PL	10500
LSTM	17500
Bi-LSTM	35000

Table 3 presents a comparison of the total learnable parameters of LSTM-PL, LSTM, and Bi-LSTM DNN based on simulations. The implementation of LSTM-PL necessitates only 10,500 learnable parameters, which is significantly lower in comparison to the number of parameters required by other DNNs such as LSTM and Bi-LSTM. Generally, LSTM networks necessitate 17,500 learnable parameters, while Bi-LSTM networks require up to 35,000 parameters. The number of learnable parameters in a DNN is directly proportional to its computational complexity [8], and in this case, it is evident that the proposed LSTM-PL DNN has the least computational complexity among all the DNNs mentioned above.

4. Conclusions

A novel approach to OFDM channel estimation using the DNN method has been developed, utilizing LSTM-PL neural networks. The proposed LSTM-PL DNN is trained offline and used online to track the channel statistics for reconstructing the transmitted symbols. The performance of the proposed DNN has been evaluated using two different pilot configurations. The experiments conducted using the LSTM-PL DNN estimator trained with Adam optimizer show superior performance compared to the conventional estimators, as well as DNN estimators like LSTM-DNN and Bi-LSTM DNN when pilots of 8 and 4 are used. Specifically, the proposed LSTM-PL DNN based approach performs better than all other estimators when only a small number of pilots are available. Additionally, the proposed method has a significantly lower computational complexity compared to that of the LSTM and Bi-LSTM DNN methods. Moreover, the proposed approach holds immense potential for enhancing communication systems, including 5G and beyond, due to its independence from prior channel knowledge. Future research may entail conducting tests on real devices or utilizing authentic training data.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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