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BiLSTM based Precise Estimation of Rayleigh Fading Channel

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Abstract

Accurate wireless channel estimation is essential for optimizing communication systems, particularly in 5G and future wireless networks. This study explores a deep learning-based approach to estimate the received power in a wireless channel, using distance, fading effects, and noise characteristics as input features. The deep neural network is designed with multiple hidden layers, incorporating batch normalization, dropout regularization, and L2 weight decay to enhance generalization and stability. The model is trained on synthetically generated channel data, simulating path loss, Rayleigh fading, and additive noise to represent realistic propagation conditions. The proposed deep learning model is trained using Mean Squared Error (MSE) loss and optimized with the Adam optimizer, along with a learning rate scheduler to improve convergence. Evaluation shows that the model achieves a low Mean Absolute Error (MAE), indicating strong predictive accuracy. The simulated and predicted power curves demonstrate minimal deviation, confirming the model's capability to generalize well across different channel conditions. Results suggest that this deep learning-based channel estimation approach effectively captures complex propagation characteristics, making it suitable for real-time applications in wireless communication systems. The model can aid in beamforming, resource allocation, and interference management, contributing to enhanced network efficiency.

Keywords: Wireless Channel Estimation, Deep Learning, Neural Networks, Rayleigh Fading, Path Loss, Received Power Prediction, Adam Optimizer, Learning Rate Scheduling.

1. Introduction

Wireless communication systems heavily rely on accurate channel state information (CSI) for optimal performance in signal transmission and reception. Traditional channel

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estimation methods, such as least squares (LS), minimum mean square error (MMSE), and pilot-based estimation, often struggle with high computational complexity, sensitivity to noise, and inefficiency in dynamic environments. To address these challenges, deep learning (DL) has emerged as a powerful tool for wireless channel estimation, providing superior adaptability, efficiency, and robustness. Deep learning-based channel estimation plays an essential role in 5G and beyond (6G) networks, particularly in massive MIMO, millimeter-wave (mmWave) communications, and reconfigurable intelligent surfaces (RIS). Future research focuses on integrating federated learning, reinforcement learning, and hybrid model-driven DL approaches to further improve channel estimation efficiency.

Deep learning methods utilize data-driven models to learn complex channel characteristics without relying on explicit mathematical models. Unlike conventional techniques, which require prior assumptions about channel statistics, DL-based approaches can automatically extract features and learn patterns from received signals. This enables them to adapt to various channel conditions (e.g., fading, interference, mobility), reduce computational complexity compared to iterative optimization-based methods, and enhance estimation accuracy by capturing non-linear relationships in wireless propagation to support real-time processing in fast-changing environments. The critical issues in selecting the techniques for wireless channel estimation include characteristics of the wireless environment, system requirements, computational constraints, overheads, and the wireless system architecture. Machine learning approaches, particularly deep learning, have shown promise in channel estimation by learning complex channel behaviors from data. These methods can adapt to various channel conditions but require substantial training data and computational resources.

Several deep learning architectures have been explored for wireless channel estimation, each providing unique advantages. Deep Neural Networks (DNNs) are commonly used to approximate channel mappings and reduce noise, improving estimation accuracy. Convolutional Neural Networks (CNNs) effectively capture spatial correlations, making them particularly useful in MIMO (Multiple-Input Multiple-Output) systems. For time-varying channels, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks excel in tracking dynamic variations in mobile environments. Autoencoders are widely applied for CSI (Channel State Information) compression and efficient feedback in massive MIMO systems, helping to reduce overhead. Additionally, Graph Neural Networks (GNNs) have emerged as a promising approach to model complex wireless networks by using graph structures to represent connectivity and interference relationships. These architectures collectively enhance the adaptability, accuracy, and efficiency of deep learning- based channel estimation.

2. Related Work

Deep learning has significantly advanced wireless channel estimation, offering innovative solutions to traditional challenges. For instance, Ye et al. [1], introduced a fully connected neural network for OFDM systems, enhancing estimation accuracy but requiring substantial training data and computational resources. In another study, Samuel et al. [2], utilized convolutional neural networks (CNNs) for joint channel estimation and signal detection in OFDM systems, demonstrating robustness to non-linear distortions, albeit with a need for exact hyperparameter tuning. He et al. [3] integrated domain knowledge into neural network design for MIMO channel estimation, reducing dependence on extensive training data but exhibiting sensitivity to model mismatches. Gao et al. [4] applied CNNs to exploit spatial structures in millimeter-wave massive MIMO systems, improving estimation accuracy, though real-time implementation posed challenges due to computational demands. Wen et al. [5], employed an autoencoder for massive MIMO CSI feedback, achieving significant compression gains but necessitating accurate channel state information at the transmitter.

Li et al. [6] utilized recurrent neural networks (RNNs) to capture temporal correlations in underwater acoustic communications, enhancing estimation accuracy in dynamic environments, albeit with prolonged training times. Huang et al. [7] utilized a denoising neural network to enhance pilot-based estimates in massive MIMO systems, improving performance in low signal-to-noise ratio scenarios, though sensitivity to hyperparameter selection was noted. Zhang et al. [8] proposed a deep neural network for joint channel estimation and signal detection in MIMO systems, achieving improved performance but facing challenges in training stability. Chen et al. [9] modeled channel characteristics in visible light communication systems using a CNN, improving estimation accuracy but limited by the need for large training datasets.

Dong et al [10], addressed rapid channel variations in OFDM systems with high mobility using a CNN, demonstrating improved performance but requiring significant computational resources. Wang et al. [12], used a neural network to compensate for non-linear distortions in OFDM systems with hardware impairments, enhancing system performance but exhibiting sensitivity to model mismatches. Guo et al. [13] separated superimposed signals in non-orthogonal multiple access (NOMA) systems using a neural network, enhancing system performance but requiring careful design to handle user interference.

In this work, the authors demonstrated the potential of deep learning to enhance wireless channel estimation. For accurate wireless channel estimation, the layers in the neural networks are iteratively tuned and optimized till the mean absolute error parameter is minimized.

3. System Model

The system model simulates a wireless communication channel by considering key physical factors affecting the signal propagation. The received power (in dB) is modeled as a function of distance, fading, and path loss, incorporating realistic wireless channel characteristics as described below in Table 1.

Table 1. System Parameters to Characterize the Wireless Channel

Simulation Parameter	Value
Number of Samples	10,000
Distance Range (m)	1 to 100 (Uniformly distributed)
Path Loss Exponent (η)	2.5 (Urban environment)
Fading Model	Rayleigh fading (Magnitude & Phase)
Noise Model	Gaussian noise (μ=0,σ=0.05)
Data Split	80% Train (8,000), 20% Test (2,000)
Feature Normalization	Standardization (Zero mean, unit variance)

- **Path Loss Model**: The received power follows a logarithmic path loss model where signal strength decreases with distance. The path loss exponent is set to 2.5, representing an urban environment.
- **Fading Effects:** The code models Rayleigh fading, commonly observed in non-line-of-sight (NLOS) wireless channels. It considers both the magnitude (Rayleigh-distributed) and the phase (uniformly distributed), capturing multipath effects.

- **Noise:** Gaussian noise with a small variance is added to account for minor variations due to interference and hardware imperfections.
- **Feature Engineering:** The input features include distance, real, and imaginary components of fading, ensuring the model learns both amplitude and phase information, which is necessary for wireless signal modeling.

The dataset consists of 10,000 samples, with 80% used for training and 20% for testing, ensuring a robust evaluation of model performance [14].

3.1 Deep Neural Network Structure

The deep learning model is a fully connected feedforward neural network (FNN) designed to predict the received power in a wireless channel based on the extracted features. Several architectural enhancements and optimization techniques are applied as shown in Table 2.

Table 2. DNN Architecture Description

Layer Type	Number of Units/Filters	Activation Function	Other Parameters
Bidirectional LSTM	128	Tanh	return_sequences=True
Batch Normalization	-	-	Normalizes activations
Dropout	-	-	rate=0.3
Bidirectional LSTM	64	Tanh	return_sequences=True
Batch Normalization	-	-	Normalizes activations
Dropout	-	-	rate=0.2
Bidirectional LSTM	32	Tanh	return_sequences=False
Dense	2	Linear	Outputs real & imaginary parts of CSI

This optimized deep learning pipeline shown in Figure 1 ensures high accuracy and robust generalization, making it well-suited for wireless communication applications such as link budget analysis, beamforming, and power control in 5G networks. The optimization parameters are listed in Table 3.

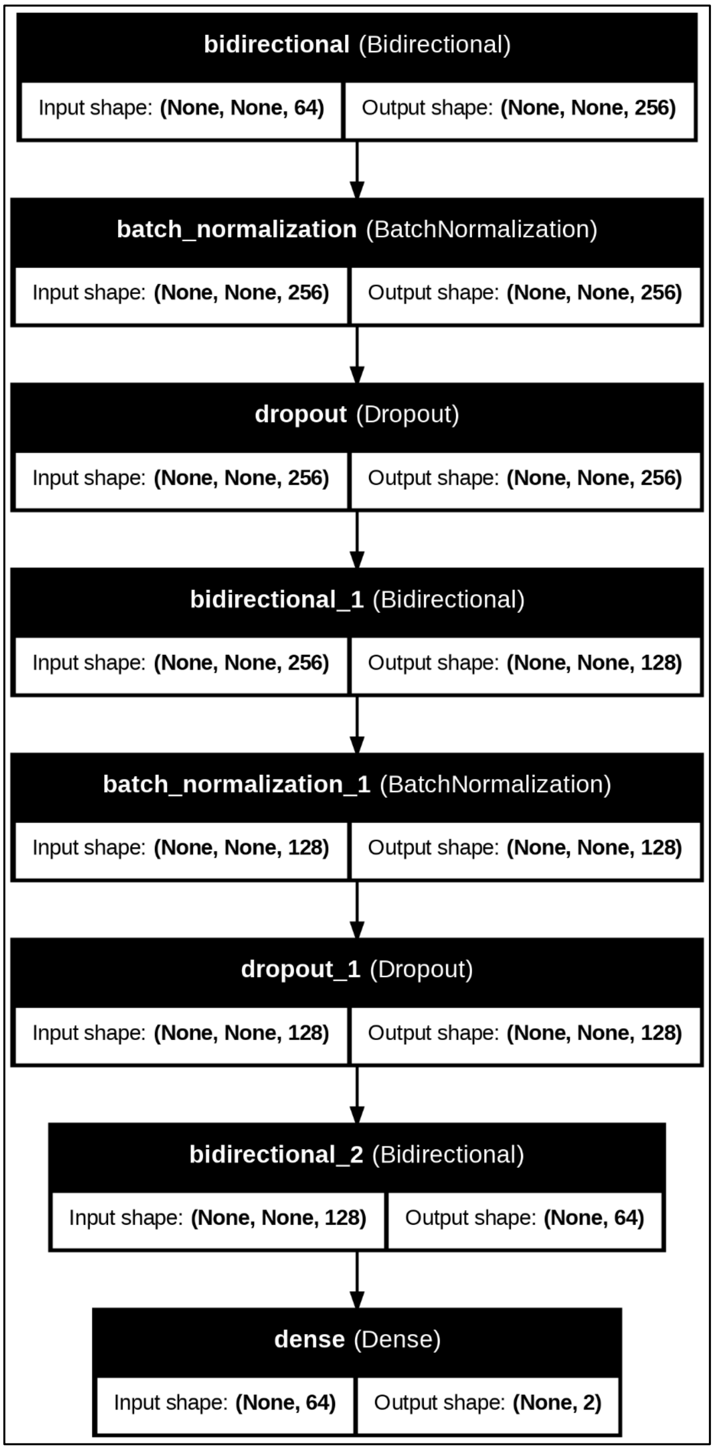

Figure 1. Proposed DL Model for Channel Estimation

Table 3. Optimization Parameters

Parameter	Description
Loss Function	Mean Squared Error (MSE)
Optimizer	Adam
Learning Rate	0.0005
Batch Size	128
Epochs	50
Validation Split	10%
Early Stopping	Enabled (patience=5, restore_best_weights=True)

4. Results and Discussion

The deep learning model effectively captures the relationship between distance, fading, and received power, achieving a low Mean Absolute Error (MAE). The training loss and validation loss converge smoothly, indicating that the model generalizes well to unseen data without overfitting. The use of batch normalization, dropout, and L2 regularization helps stabilize learning, ensuring that the network does not memorize noise but rather learns meaningful patterns in the wireless channel data. The Root Mean Squared Error (RMSE) further confirms the accuracy of the predictions as shown in Figure 2 , highlighting the model's ability to approximate real-world wireless propagation conditions. In wireless channel estimation, the estimation error quantifies the discrepancy between the predicted channel state information (CSI) and the actual channel conditions. Deep learning (DL) models have been increasingly employed for channel estimation due to their ability to capture complex patterns in data. Mismatches between training and actual channel conditions can lead to increased estimation errors. For example, when the variance of the training data is lower than that of the actual channel ($\eta < 1$), the MSE of DL estimators increases, highlighting the importance of accurate training data. Python-based custom simulation was employed due to their flexibility in defining channel models and integrating with deep learning workflows.

The simulated vs. predicted values plot demonstrates that the predicted received power closely follows the actual received power across different sample indices. The minimal deviation between the two curves suggests that the model is capable of accurately estimating the wireless channel response.

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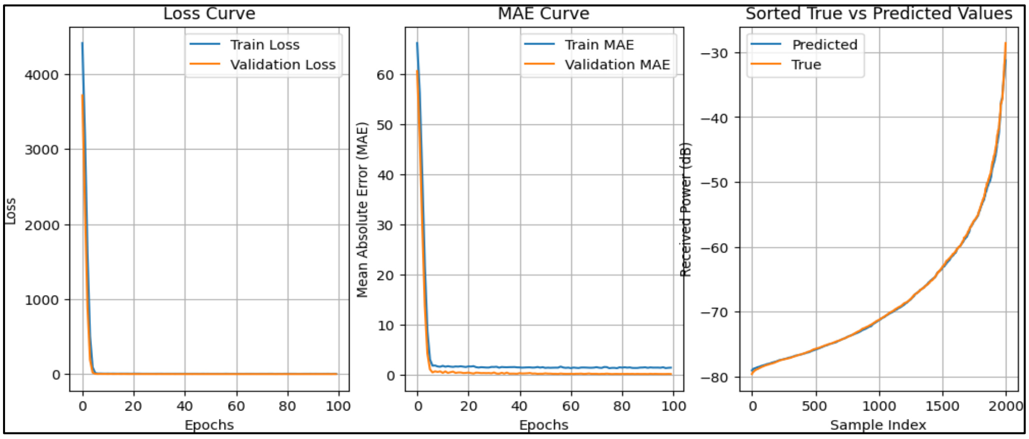

Figure 2. Loss and Error Performance of the Proposed DL Model for Channel Estimation

However, slight variations in the predictions could be attributed to random noise in the dataset and the stochastic nature of fading effects. In wireless channel estimation, quantifying the deviation between predicted and actual channel states is essential for evaluating model performance. This deviation, or estimation error, is typically determined using various metrics, depending on the system's requirements and the nature of the data. Estimating the error between predicted and actual channel states that is essential for evaluating the performance of channel estimation models.

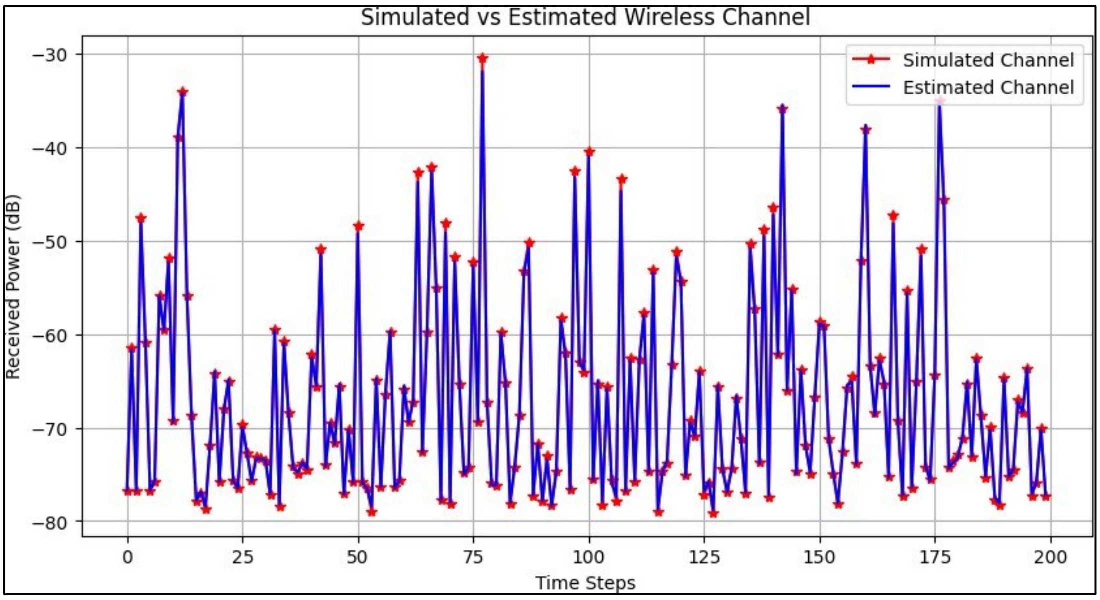

Figure 3. Simulated and Estimated Channel Values for 200 Time Steps

Finally, the simulated vs. estimated channel plot as in Figure 3 over time indicates that the model can track variations in received power over different time steps, capturing both large-scale path loss effects and small-scale fading fluctuations. These results suggest that the proposed deep learning approach can be applied to real-time channel estimation and power prediction in wireless networks, potentially improving beamforming, resource allocation, and interference management in 5G and beyond.

5. Conclusion

This study demonstrates the effectiveness of a deep learning approach for wireless channel estimation in Rayleigh fading environments, where a deep neural network, trained on data simulating realistic channel impairments, accurately predicts received power. The model achieves a low Mean Absolute Error and closely aligns simulated and predicted power curves, indicating strong predictive accuracy and generalization. These results highlight deep learning's potential to provide accurate channel estimates for optimizing 5G and future wireless networks; however, future work should validate the model with real-time data and explore its robustness in more complex scenarios and its feasibility for real-time implementation.

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