Optimizing Least Squares Channel Estimation using Deep Learning in 5G NR PUSCH

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***Abstract*—This paper proposes a Deep Neural Network (DNN) assisted channel estimator for 5G New Radio (NR) Single-Input Single-Output (SISO) Physical Uplink Shared Channel (PUSCH) system. Pilot-based Least Squares (LS) channel estimation is performed using Demodulation Reference Signals (DMRS), where the initial estimates at pilot positions serve as input to the DNN, and the resulting optimized estimates are post-processed using spline interpolation to obtain the channel response across all time and frequency resources. Unlike the minimum mean square error (MMSE) estimator, which requires prior knowledge of channel covariance and noise variance, the proposed DNN learns a superior non-linear mapping purely from data, eliminating the need for channel statistics at inference. The performance is evaluated in terms of Normalized Mean Square Error (NMSE) and Bit Error Rate (BER) over a range of Signal-to-Noise Ratios (SNRs) under the CDL-B and TDL-B channel models. The proposed DNN-based channel estimator demonstrates a significant reduction in NMSE over the conventional LS estimator and closely approaches the optimal MMSE performance, confirming its effectiveness as a robust and efficient estimation scheme for practical 5G NR PUSCH systems.**

***Index Terms*—5G New Radio, PUSCH, DNN, Channel Estimation, NMSE.**

I. Introduction

The Fifth Generation (5G) New Radio (NR) standard, and its evolution toward 5G-Advanced, has been designed to support diverse service requirements such as enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), and massive machine-type communications (mMTC) [1]. To address these demands, 5G NR employs a flexible and scalable physical layer architecture, enabling advanced modulation, coding, and multi-antenna transmission techniques in both downlink (DL) and uplink (UL) communications. As wireless networks evolve toward 5G-Advanced and future 6G systems, Artificial Intelligence (AI) and Machine Learning (ML) are emerging as powerful tools for enhancing the performance of the Radio Access Network (RAN). Standardization efforts by the 3rd Generation Partnership Project (3GPP), particularly in Release 18 and Release 19, are increasingly exploring AI-native air interfaces where learning-based techniques can assist key physical-layer operations such as channel estimation, beam management, and positioning. At the same time, the growth of edge computing enables low-latency inference directly within the network infrastructure, making the practical deployment of AI-driven signal processing more feasible [2].

Among these applications, improving channel estimation remains a critical research focus. In practical cellular systems, uplink transmission is constrained by limited user equipment (UE) transmit power and is more susceptible to channel impairments, which makes robust receiver design at the base station a key challenge. Inaccurate channel estimation can significantly degrade coherent detection and link adaptation, ultimately affecting overall system reliability. Therefore, enhancing channel estimation accuracy can help mitigate the impact of uplink impairments and improve receiver robustness. In this context, deep learning-based approaches offer promising capabilities to learn complex channel characteristics and improve estimation performance, potentially enabling more reliable uplink communication across diverse 5G NR deployment scenarios and numerologies.

In practical wireless communication systems, channel estimation is often affected by noise, hardware imperfections, and other unknown disturbances. Traditionally, pilot-assisted techniques such as Least Squares (LS) and Minimum Mean Square Error (MMSE) estimation have been proposed in the literature for orthogonal frequency division multiplexing (OFDM) channel estimation. In [3], LS and MMSE are derived. LS is widely used due to its simplicity. However, this estimator does not explicitly incorporate noise characteristics into the estimation process, potentially resulting in reduced accuracy in real-world environments. As an alternative approach, MMSE estimation provides improved estimation accuracy by incorporating statistical information about the channel and noise. However, MMSE estimation suffers from high computational complexity and requires prior knowledge of the second-order statistics of both the channel and the noise. Recent studies have investigated the use of deep learning to enhance traditional channel estimation techniques [4]. Prior work has explored using deep neural networks (DNNs) to improve traditional LS channel estimation in OFDM systems, particularly under vehicular channel conditions [5]. However, to the best of our knowledge, these approaches do not take into account the standardized 5G NR signal structure defined by the 3GPP.

In contrast, this work focuses on the application of learning-assisted channel estimation within the 5G NR framework. Specifically, we consider the uplink channel estimation process based on Demodulation Reference Signals (DMRS) defined by the 3GPP standard. By integrating a DNN-based refinement stage with the conventional LS estimator, the proposed

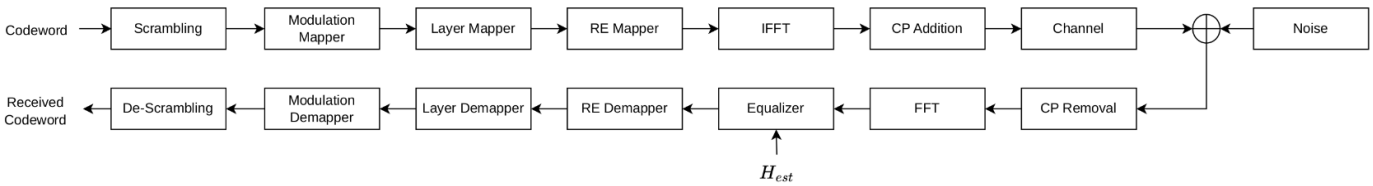

Fig. 1: 5G NR PUSCH Transceiver chain

approach aims to improve channel estimation accuracy and enhance receiver robustness in practical 5G NR uplink scenarios.

The rest of the paper is organized as follows: Section II describes the system model, Section III presents the channel estimation schemes, and Section IV provides the simulation results and analysis. Lastly, Section V outlines the conclusion of this paper.

II. System Model

We consider a single-user 5G NR uplink transmission over the PUSCH as shown in Fig. 1, employing CP-OFDM modulation. We assume a transmission slot consisting of K active subcarriers and M OFDM symbols.

Let a single transmit and receive antenna be considered. The frequency-domain signal transmitted is represented by the matrix $\mathbf{S} \in \mathbb{C}^{K \times M}$, which contains both data symbols and DMRS placed as per 3GPP 5G NR specifications [6]. An inverse fast Fourier transform (IFFT) operation is applied independently to each column of $\mathbf{S}$, followed by a cyclic prefix insertion, resulting in the time-domain waveform $\mathbf{s}$.

The wireless channel between the transmitter and receiver is modeled as a frequency-selective fading channel with a finite impulse response of length L, denoted by $\mathbf{h} \in \mathbb{C}^{L}$. The channel is normalized such that the average received signal power is unity. Assuming the cyclic prefix length exceeds the maximum channel delay spread, the received time-domain signal can be written as,

$$\mathbf{y} = \mathbf{s} \circledast \mathbf{h} + \mathbf{z}, \tag{1}$$

where $\circledast$ denotes circular convolution, and additive noise at the receiver is modelled as a complex Gaussian random process $\mathbf{z} \sim \mathcal{CN}(\mathbf{0}, \sigma^2\mathbf{I})$.

After cyclic prefix removal and Fast Fourier transform (FFT), the received frequency-domain signal is expressed as,

$$\mathbf{Y} = \mathbf{S} \odot \mathbf{H} + \mathbf{Z}, \tag{2}$$

where $\odot$ denotes the element-wise multiplication, $\mathbf{H} \in \mathbb{C}^{K \times M}$ represents the channel frequency response, and $\mathbf{Z}$ is the frequency-domain representation of the noise.

III. Channel Estimation

Accurate channel estimation is essential for coherent demodulation of uplink data transmissions in 5G NR. The PUSCH DMRS serves as a user-specific reference signal, multiplexed with PUSCH data symbols and transmitted exclusively in uplink-allocated slots, making it the basis for channel estimation at the receiver. Both the PUSCH and the associated DMRS undergo the same precoding. Higher-layer DMRS parameters, including configuration type, mapping type, and the number of additional DMRS positions, determine the frequency and time domain placement of the DMRS within the resource grid. These parameters are signaled to the UE through Downlink Control Information (DCI) on the Physical Downlink Control Channel (PDCCH) as part of Radio Resource Control (RRC) signaling.

The PUSCH DMRS employs a comb-type pilot structure that balances channel estimation accuracy and uplink throughput. Additional DMRS positions can be configured by the base station to support channel-critical scenarios, such as high-mobility environments. The Fig. 2 PUSCH DMRS resource grid corresponds to an uplink transmission employing a single DMRS port. The DMRS occupies OFDM symbols 3 and 12 within the slot with a comb-type frequency-domain structure, enabling reliable channel estimation while efficiently utilizing time-frequency resources for coherent PUSCH demodulation.

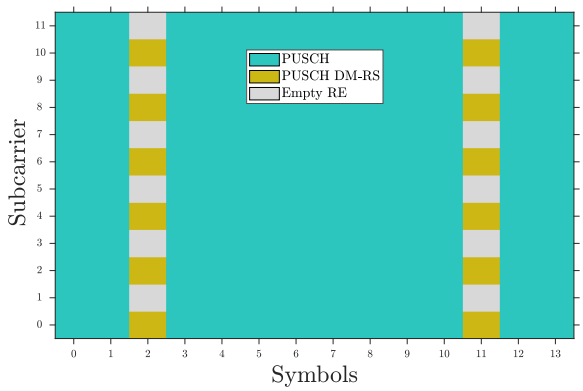

Fig. 2: PUSCH DMRS Resource grid

A. Conventional Channel estimation schemes

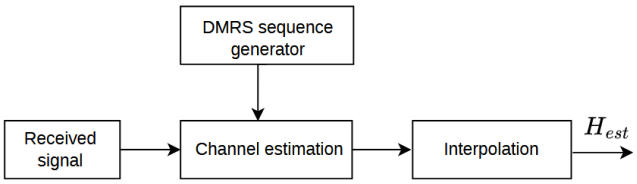

Fig. 3: Channel estimation block

The received frequency-domain uplink IQ samples are sent to the channel estimator block as shown in Fig. 3, where channel estimation is performed using the generated DMRS sequences. The estimated channel values at the pilot subcarriers are then extended to all subcarriers using spline interpolation.

1) LS Channel estimation: The Least Squares (LS) channel estimation is performed at each DMRS subcarrier by exploiting the known transmitted DMRS symbols. Specifically, the LS estimate of the channel frequency response is obtained by dividing the received DMRS symbols by the corresponding transmitted reference symbols on a per-subcarrier basis. This process yields raw channel estimates at the DMRS resource elements for each transmit–receive antenna pair.

Let $\mathcal{M}$ denote the set of OFDM symbols containing DMRS. For each symbol index $m \in \mathcal{M}$, let $Y(m)$ denote the received complex sample and $S(m)$ denote the transmitted DMRS symbol at the DMRS subcarriers. The LS estimated channel frequency response at the DMRS subcarriers of the m^{th} OFDM symbol is denoted by $\hat{H}_{LS}(m)$. The LS channel estimate is given by [7],

$$\hat{H}_{LS}(m) = \frac{Y(m)}{S(m)}, \tag{3}$$

where $Y(m)$, $S(m)$, and $\hat{H}_{LS}(m)$ are complex-valued vectors of dimension $K_{\text{DMRS}} \times 1$. Let $H(m)$ denote the true channel frequency response at the m^{th} OFDM symbol. Substituting $Y(m)$,

$$\hat{H}_{LS}(m) = \frac{S(m)H(m) + Z(m)}{S(m)} = H(m) + \frac{Z(m)}{S(m)}. \tag{4}$$

The channel estimation error is

$$e(m) = \hat{H}_{LS}(m) - H(m) = \frac{Z(m)}{S(m)}. \tag{5}$$

The mean square error (MSE) is therefore

$$MSE_{LS} = \mathbb{E}\left[|e(m)|^2\right] = \mathbb{E}\left[\left|\frac{Z(m)}{S(m)}\right|^2\right] = \frac{\mathbb{E}[|Z(m)|^2]}{|S(m)|^2}. \tag{6}$$

Let $P_{\text{DMRS}} = |S(m)|^2$ denote the power of the DMRS symbols. Since $\mathbb{E}[|Z(m)|^2] = \sigma^2$ we obtain,

$$MSE_{LS} = \frac{\sigma^2}{|S(m)|^2} = \frac{\sigma^2}{P_{\text{DMRS}}}. \tag{7}$$

Let $\mathbb{E}[|H(m)|^2] = \sigma_H^2$ denote the channel power. Substituting the above result into the normalized mean square error (NMSE) definition, we obtain [8],

$$NMSE_{LS} = \frac{\mathbb{E}[|H(m) - \hat{H}_{LS}(m)|^2]}{\mathbb{E}[|H(m)|^2]} = \frac{\sigma^2}{P_{\text{DMRS}}\sigma_H^2}. \tag{8}$$

For a normalized channel with $\sigma_H^2 = 1$, the theoretical NMSE of the LS channel estimator becomes

$$NMSE_{LS} = \frac{\sigma^2}{P_{\text{DMRS}}}. \tag{9}$$

The LS estimator is computationally simple and can be obtained using only one multiplication per subcarrier. However, its performance is limited since it does not exploit the structural properties of the wireless channel.

2) MMSE Channel estimation: The MMSE channel estimator exploits the second-order statistics of the channel to reduce the estimation error. Let $\mathbf{R}_H = \mathbb{E}[H(m)H(m)^H]$ denote the channel correlation matrix at the DMRS subcarriers. The MMSE estimate of the channel frequency response is given by [7],

$$\hat{H}_{MMSE}(m) = \mathbf{R}_H \left(\mathbf{R}_H + \sigma^2\mathbf{I}\right)^{-1} \hat{H}_{LS}(m), \tag{10}$$

where $\hat{H}_{LS}(m)$ denotes the LS channel estimate and $\mathbf{I}$ is the identity matrix. Substituting (4) in (10), the MMSE estimator becomes,

$$\hat{H}_{MMSE}(m) = \mathbf{R}_H \left(\mathbf{R}_H + \sigma^2\mathbf{I}\right)^{-1} \left(H(m) + \frac{Z(m)}{S(m)}\right). \tag{11}$$

Let $\mathbf{W} = \mathbf{R}_H \left(\mathbf{R}_H + \sigma^2\mathbf{I}\right)^{-1}$ denote the MMSE weighting matrix. Then

$$\hat{H}_{MMSE}(m) = \mathbf{W}\left(H(m) + \frac{Z(m)}{S(m)}\right). \tag{12}$$

The NMSE of the MMSE estimator is defined as,

$$NMSE_{MMSE} = \frac{\mathbb{E}\left[\|H(m) - \hat{H}_{MMSE}(m)\|^2\right]}{\mathbb{E}\left[\|H(m)\|^2\right]}. \tag{13}$$

Let λ_i denote the eigenvalues of the channel correlation matrix $\mathbf{R}_H$. Using the eigenvalue decomposition of $\mathbf{R}_H$, the theoretical NMSE of the MMSE estimator can be expressed as,

$$NMSE_{MMSE} = \frac{\sum_{i=1}^{M} \frac{\lambda_i \sigma^2}{\lambda_i + \sigma^2}}{\sum_{i=1}^{M} \lambda_i}. \tag{14}$$

While the MMSE estimator achieves improved estimation performance compared to the LS estimator, it requires prior knowledge of the channel's second-order statistics and involves matrix inversion operations, leading to increased computational complexity.

B. Deep Neural Network-assisted Channel Estimation

In wireless channel estimation, conventional LS estimates are often corrupted by noise, resulting in degraded estimation accuracy. Deep Neural Networks (DNNs) have emerged as an effective solution to address this limitation [9]. A DNN is a supervised learning model consisting of multiple layers of interconnected neurons, where each neuron performs a weighted linear transformation followed by a nonlinear activation function. Using a labeled dataset of input-output pairs, the

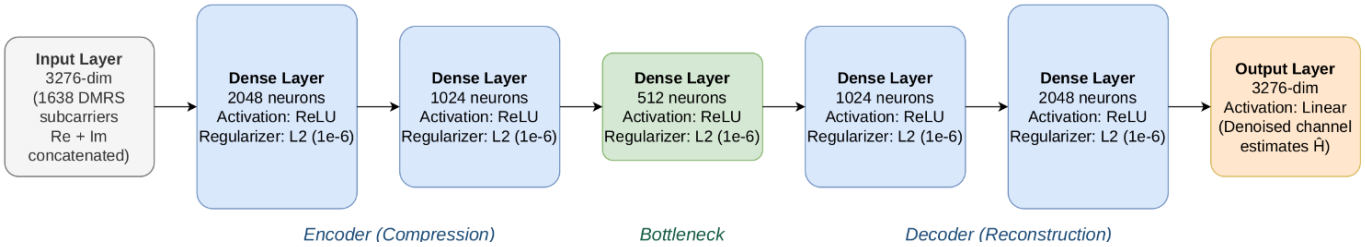

Fig. 4: The proposed DNN architecture

network learns a nonlinear mapping by iteratively updating its parameters through backpropagation to minimize a predefined loss function [10]. By training the DNN with pairs of noisy LS estimates and their corresponding true channel coefficients, $(\hat{H}_{LS}, H)$, the model learns to suppress noise and generate channel estimates that more closely approximate the actual channel response [11].

As illustrated in Fig. 4, the proposed network employs a supervised autoencoder-inspired DNN. The encoder progressively compresses the noisy input into a compact bottleneck representation, forcing the network to discard noise artifacts while retaining the underlying channel structure, and the decoder symmetrically reconstructs the refined channel estimate at the original input dimension.

A dataset of 5,000 channel realizations is generated using MATLAB R2025b, ensuring standardized and physically consistent modeling in accordance with 5G NR specifications. We use 70% data for training, 15% as the validation set, and 15% data for testing. The proposed DNN is having a batch size of 16 and an epoch count of 1000 is used for training at a learning rate of 5×10^{-4}. All hidden layers use the rectified linear unit (ReLU), i.e., $f_a(x) = max(0, x)$, which helps avoid the vanishing gradient problem, while the output layer keeps a linear activation to maintain the full dynamic range of the channel coefficients. To prevent overfitting, an $L2$ regularizer with a coefficient of 10^{-5} is added to all hidden layers. The model is trained using the ADAM optimizer with MSE loss, and a ReduceLROnPlateau scheduler that automatically lowers the learning rate when validation loss stagnates. Only the weights from the epoch with the lowest training and validation MAE are saved, ensuring the best-performing model is deployed.

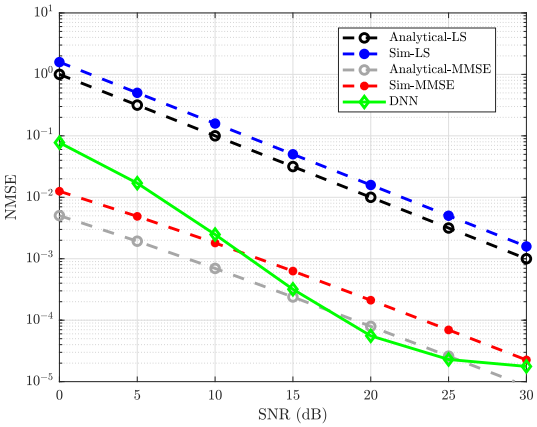

Fig. 5: NMSE vs. SNR for CDL-B Channel model

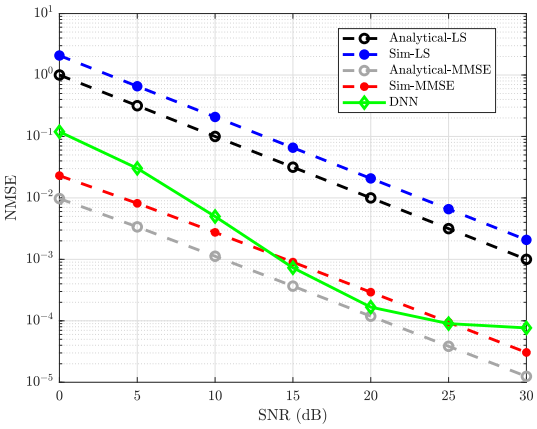

Fig. 6: NMSE vs. SNR for TDL-B Channel model

IV. Simulation Results and Analysis

In this section, we present the link-level simulation results for a 5G NR PUSCH system. The simulations are conducted using MATLAB R2025b 64-bit, and the parameters are selected to ensure compliance with the 3GPP 5G NR specifications. The simulation parameters are summarized in Table I.

A. NMSE Performance

Fig. 5 and Fig. 6 show the NMSE performance versus SNR for different channel estimation techniques under CDL-B and TDL-B channel profiles, respectively. As SNR increases, all methods exhibit improved NMSE performance. The LS estimator performs the worst due to its sensitivity to noise, while MMSE achieves significantly lower NMSE by utilizing channel statistics. The proposed DNN-assisted estimator consistently outperforms conventional LS and achieves performance comparable to, or better than, MMSE, particularly at moderate-to-high SNRs.

B. BER Performance

Fig. 7 and Fig. 8 illustrate the BER performance for different channel estimation schemes for CDL-B and TDL-B

TABLE I: Simulation parameters

Parameter	Value
Bandwidth	100 MHz
Subcarrier spacing (SCS)	30 kHz
Number of RBs	273
Modulation, Coderate	QPSK, 679/1024
DMRS Configuration type	1
DMRS length	1
Channel profile	CDL-B & TDL-B
Delay spread	30 ns
Doppler shift	10 Hz
SNR range	$[0, 30]$ dB

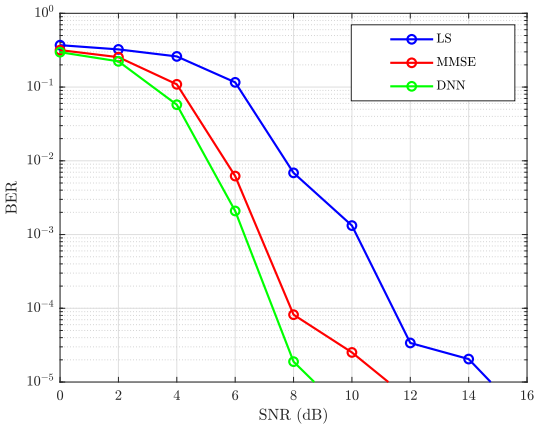

Fig. 7: BER vs. SNR for CDL-B Channel model

channel models, respectively. For the CDL-B channel model, the proposed DNN-assisted LS attains a BER of 10^{-4} at around 7 dB, whereas the MMSE and LS methods achieve the same BER at approximately 8 dB and 11 dB, respectively. This corresponds to an SNR gain of 1 dB over MMSE and 3 dB over LS, highlighting the effectiveness of the proposed DNN-assisted approach.

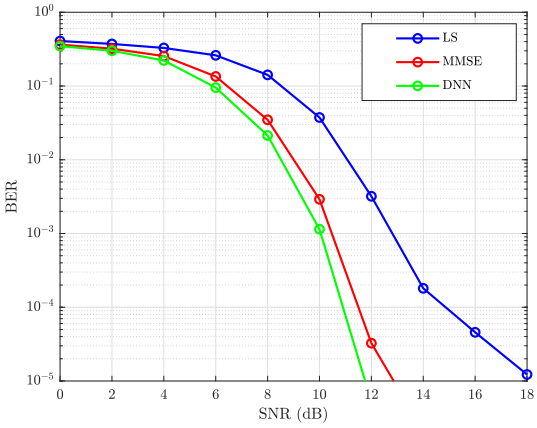

Fig. 8: BER vs. SNR for TDL-B Channel model

C. Complexity analysis

The LS estimator performs element-wise division at each DMRS subcarrier, resulting in a complexity of $\mathcal{O}(K_{\text{DMRS}})$, making it the least complex but most noise-sensitive method. The MMSE estimator requires inversion of $K_{\text{DMRS}} \times K_{\text{DMRS}}$ covariance matrix, leading to a complexity of $\mathcal{O}({K_{\text{DMRS}}}^3) \approx 4.4 \times 10^9$ operations for $K_{\text{DMRS}} = 1638$. The proposed DNN estimator requires approximately 18.66×10^6 MAC operations per forward pass, significantly less than MMSE.

V. Conclusion

Our work explores a deep learning assisted channel estimation approach for the 5G NR PUSCH. We focus on improving conventional LS channel estimates using DNN. The proposed method is evaluated in terms of NMSE, BER and computational complexity, and compared with conventional LS and MMSE estimators. The results show that the DNN-assisted approach achieves near-MMSE performance across a wide range of SNRs while significantly reducing the computational complexity. Overall, the study demonstrates that combining learning-based refinement with standard 5G NR channel estimation, provides a practical and efficient solution for robust uplink communication in real-world systems.

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