CNN-Based Channel Estimation for Extreme Scenarios in 6G and Beyond

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***Abstract*—Channel estimation plays a critical role in wireless communication, especially under extreme scenarios that pose significant challenges to reliable communication. These challenges are expected to be more severe in 6G and beyond due to the adoption of higher frequencies (millimeter-wave and terahertz bands) and the integration of high-speed terrestrial and non-terrestrial networks for ubiquitous connectivity. Conventional channel estimation techniques, such as the Least Squares (LS) and Minimum Mean Squared Error (MMSE) estimators struggle under these conditions due to their reliance on linear models and sensitivity to noise. This research investigates the use of a Convolutional Neural Network (CNN) for channel estimation in extreme scenarios. The proposed CNN architecture captures the spatial and temporal features, as well as the non-linear patterns in the time-frequency resource grid of wireless channels, enabling robust and efficient channel estimation. Performance comparisons between the CNN-based and conventional channel estimation techniques were conducted under varying Doppler shift, delay spread, and signal-to-noise ratio (SNR) conditions. The results demonstrate that the CNN-based channel estimator significantly outperforms conventional methods, maintaining a low mean squared error (MSE) even under severe conditions. These findings highlight CNN-based channel estimation as a robust and adaptable solution for next-generation networks.**

Keywords—6G, Channel estimation, CNN, deep learning, extreme scenarios, frequency selective and time-varying channels, high mobility, Doppler effects, next generation networks.

I. Introduction

The next generation of wireless networks, 6G and beyond, promises transformative advancements beyond previous-generation networks. They are envisioned to deliver extreme data rates, ultra-low latency, increased reliability and efficiency, massive connectivity and better quality of service (QoS). These advanced capabilities will pave the way for transformative technologies, including holographic communication, extended reality (XR), autonomous vehicles, remote surgery, unmanned aerial vehicles (UAVs), and smart cities [1]. 6G also aims to achieve ubiquitous connectivity and bridge the digital divide by integrating the existing terrestrial network with non-terrestrial networks (NTN), thereby forming a space-air-ground integrated network (SAGIN) [2].

Despite these advantages, next generation networks would face significant challenges in ensuring reliable and efficient communication in extreme scenarios. These extreme scenarios are characterized by multipath fading, high Doppler effects, severe attenuation or path loss at millimeter wave (mmWave) and terahertz (THz) frequencies, which presents significant challenges for maintaining reliable and efficient communication [3].

As signals propagate through the wireless channel, they can be affected in diverse ways. Channel estimation, a critical component of wireless communication, plays a vital role in predicting the channel's behavior to facilitate accurate signal equalization and detection. However, the frequency-selective and rapidly time-varying nature of wireless channels in extreme scenarios poses significant challenges to channel estimation accuracy.

Traditional channel estimation techniques, including Least Squares (LS) and Minimum Mean Square Error (MMSE), have been instrumental in addressing channel estimation in previous-generation networks [4]. However, their reliance on linear mathematical models, sensitivity to noise, high computational complexity and inability to adapt to rapidly changing channel conditions render them less effective in extreme scenarios where the channel conditions pose significant challenges. These limitations have prompted researchers to explore more advanced and adaptable solutions.

In recent years, deep learning (DL) has emerged as a promising solution for addressing the challenges in wireless communications, offering data-driven approaches to tackle complex tasks such as channel estimation, signal detection, and beamforming [5]. DL models can exploit spatial, temporal, and spectral correlations within the communication channels, offering robust channel estimation with reduced computational overhead. Hence, researchers are exploring the potential of DL for channel estimation [6].

Among various DL architectures, Convolutional Neural Networks (CNNs) have demonstrated outstanding capabilities in channel estimation tasks [7]. CNNs can effectively capture spatial features and complex non-linear patterns in channel responses, enabling accurate and adaptable channel estimation across diverse and challenging scenarios compared to conventional methods. Unlike conventional techniques that rely on mathematical models and assumptions, CNN-based channel estimators learn the relationship between received signals and channel conditions directly from data, making them adaptable to non-linear, dynamic, and extreme scenarios.

While existing studies have highlighted the advantages of CNN-based channel estimation over conventional methods in applications such as millimeter-wave (mmWave) and massive multiple input multiple output (mMIMO) systems, there is limited research exploring their performance in extreme scenarios, which poses significant challenges to channel estimation accuracy. These extreme scenarios with high Doppler shifts, delay spread, and low SNR are prevalent in dense urban areas, vehicular communications, high-speed terrestrial and non-terrestrial networks, making this an essential area of research for 6G and beyond.

Hence, this research addresses this critical gap in channel estimation by evaluating the performance of CNN-based method under extreme conditions anticipated in 6G and beyond. By systematically comparing CNN-based models with conventional techniques, this study highlights the advantages of CNN in tackling challenges such as high mobility, severe multipath fading, and low SNR. The findings provide valuable insights into the adaptability, efficiency, and accuracy of CNN-based channel estimation, establishing it as a superior alternative to conventional methods for reliable communication in next-generation networks.

The contributions of this study are summarized as follows:

- A realistic training dataset was generated for channel estimation using standard-compliant waveforms and channel models from MATLAB's 6G Exploration Library. This dataset provides a reliable representation of wireless channel conditions in extreme scenarios.
- A CNN-based channel estimation model was developed to effectively capture the non-linear, complex and dynamic patterns in wireless channels. The model demonstrates high accuracy in estimating the wireless channel, even in challenging conditions.
- A detailed comparative analysis of the CNN-based channel estimation model and conventional techniques (interpolation and LS) was conducted across various scenarios. This analysis highlights the strengths and limitations of each technique, providing valuable insights into the effectiveness of CNN-based methods for extreme scenarios anticipated in 6G and beyond.

The rest of this article is organized as follows: Section II reviews related work on DL-based channel estimation. Section III presents the system model, CNN model, and dataset description. Section IV discusses the simulation results and comparative analysis. Finally, Section V concludes the article and outlines potential future research directions.

II. Related Work

Deep learning has emerged as a transformative approach for channel estimation in wireless communication systems, offering significant advantages over traditional methods. Techniques such as CNNs and Recurrent Neural Networks (RNNs) have demonstrated their potential to address the limitations of conventional estimators [8]. By enabling models to adapt dynamically to rapidly changing channel conditions, DL provides robust solutions for high-mobility scenarios and complex interference patterns, without relying on mathematical channel models. CNNs are well-suited for channel estimation due to their ability to capture spatial and temporal correlations in input data. This makes them effective in extracting meaningful features while suppressing noise. Treating the wireless channel as an image is an innovative approach adopted to leverage CNNs for channel estimation.

In [7], a DL pipeline combining image super-resolution (SR) and image restoration (IR) was proposed. The wireless channel was represented as an image, and the pipeline utilized a Learned Denoising-Based Approximate Message Passing (LDAMP) network. This network integrated a CNN-based denoiser with a linear estimator for channel estimation. The approach achieved lower normalized mean squared error (NMSE) and higher spectral efficiency than compressed sensing algorithms. However, it assumed static channels and did not account for hardware impairments, limiting its applicability in high-mobility scenarios. Similarly, in [9], received pilot symbols and fast-fading channel responses were treated as low-resolution images. A super-resolution CNN enhanced their resolution, followed by a denoising network to refine the estimates. While this technique performed comparably to the MMSE and outperformed approximations of linear MMSE, its performance degraded at higher SNRs.

Authors in [10] proposed a fast super-resolution CNN (FSRCNN) for channel estimation in mines. This method used the LS channel estimation matrix as a low-resolution input image and the true channel state information (CSI) as a high-resolution output during training. This approach outperformed traditional LS estimators in scenarios with limited pilot symbols and low SNRs. In [11], a DL framework integrating hybrid beamforming and channel estimation was introduced. By leveraging channel statistics and CNNs, the framework effectively obtained hybrid precoders, demonstrating the capability of DL to address both channel estimation and beamforming challenges in wireless systems.

Other DL approaches, such as Generative Adversarial Networks (GANs) [12] and Autoencoders [13], have also been explored for channel estimation. GANs are often employed to generate synthetic datasets to augment training data, whereas Autoencoders are utilized for dimensionality reduction, feature extraction, or even end-to-end signal detection. Overall, the existing literature has highlighted the significance of DL architectures such as CNN, in addressing channel estimation challenges. However, more research is needed to explore the potentials of CNN in challenging scenarios.

III. System Model

The system model captures the complexities of next generation wireless networks, including high-mobility, multipath fading and low SNR. The model comprises three primary components: transmitter, channel, and receiver. From these components the dataset is collected to train the CNN, which is later deployed as shown in Fig. 1.

A simplified model considers the received signal as an attenuated and delayed version of the transmitted signal. If $x(t)$ is the transmitted signal, then the received signal is:

$$y(t) = h \cdot x(t - \tau) \quad (1)$$

where h represents the channel attenuation factor, which is dependent on the propagation medium, frequency and transmitter/receiver gains, while τ represents the delay which is dependent on the velocity of the electromagnetic wave.

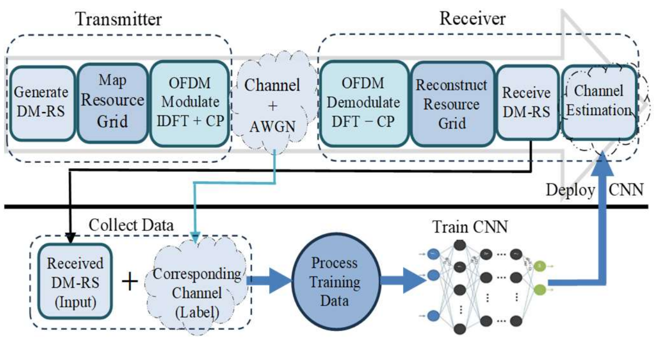

Fig. 1. Block Diagram of the System Model

In reality, the received signal $y(t)$ is composed of multiple reflected and scattered versions of the transmitted signal, each with varying attenuation and delay.

$$y(t) = \sum_{l=0}^{L-1} h_l(t) \cdot x(t - \tau_l) \tag{2}$$

where l is a specific path (tap), and L is total number of paths.

Furthermore, relative motion between the transmitter and receiver introduces a Doppler frequency shift, which alters the signal's wavelength or frequency. This Doppler effect significantly influences signal path loss and fading caused by multipath propagation. Consequently, the channel characteristics (h_l and τ_l) become time-varying, denoted as $h_l(t)$ and $\tau_l(t)$, respectively. Considering the multipath propagation, the Doppler effect and the noise $n(t)$, the received signal at a specific time t can be expressed as:

$$y(t) = \sum_{l=0}^{L-1} h_l(t) \cdot x(t - \tau_l(t)) + n(t) \tag{3}$$

Thus, the received signal is affected by the channel, which is characterized by the number of paths, the time-varying nature of the channel coefficients, and the time delays associated with each path. Hence, the multipath time-varying channel can be expressed as [14]:

$$h(t, \tau) = \sum_{l=0}^{L-1} A_l(t) \delta(\tau - \tau_l(t)) \tag{4}$$

where $A_l(t)$ denotes the time-varying amplitude of the lth channel path or tap, and L is the total number of paths.

The tapped delay line (TDL) models, where each tap corresponds to a distinct multipath component with associated delay and Doppler spectrum, are adopted. These models are parameterized based on the 3rd Generation Partnership Project (3GPP) TR 38.901 specifications [15]. The upper mid-band (FR3) ranging from 7.125 GHz to 24.25 GHz, which is under investigation for 6G is employed in this research. Therefore, the received signal is given by:

$$y(t) = \sum_{l=0}^{L-1} \alpha_l \cdot e^{j2\pi f_{D,l} t} \cdot x(t - \tau_l(t)) + n(t) \tag{5}$$

where α_l is the amplitude (gain) of the l-th path, which may include frequency-dependent attenuation and blockage effects for high-frequency scenarios, $f_{D,l}$ is the Doppler frequency shift for the l-th path, $x(t - \tau_l(t))$ is the transmitted signal delayed by $\tau_l(t)$.

The multipath components can be grouped into clusters, where each cluster represents a set of rays with similar delays and angles, as defined in the 3GPP Geometry-based Stochastic Channel Model (GBSM). The TDL profiles include non-line-of-sight (NLOS) profiles A, B, and C, characterized by multiple scattered paths, as well as line-of-sight (LOS) profiles D and E, where a dominant direct path exists. To simulate realistic and extreme 6G scenarios, the channel model extends the 3GPP framework by incorporating larger subcarrier densities, wider delay spreads, and increased Doppler shifts, enabling the evaluation of communication performance under very high mobility and dynamic propagation scenarios.

A. Dataset Description

The dataset for this research was carefully designed to reflect the spatial, temporal, and spectral variations expected in extreme scenarios in 6G and beyond. It was generated (as shown in Fig. 1), using MATLAB's 6G Exploration Library [16]. By employing a single-input single-output (SISO) system, the physical downlink shared channel (PDSCH) and the demodulation reference signals (DM-RS). Each dataset sample represents a resource grid in the time-frequency domain, comprising 612 subcarriers and 14 OFDM symbols.

The resource grids represent the allocation of resources in the time-frequency domain. Each element in the grid corresponds to a specific time slot and frequency subcarrier. These elements contain complex numbers representing the channel characteristics at that specific time and frequency.

The dataset was generated through 1024 unique signal transmissions, with each simulation incorporating randomized channel conditions, including varying delay spreads, Doppler shifts, and SNR values. These parameters were selected to represent diverse scenarios, including extreme conditions, ensuring rigorous evaluation of the proposed CNN model. The simulation parameters are outlined in Table 1.

To prepare the data for CNN processing, the complex-valued resource grids (612×14 matrices) were split into two real-valued matrices representing the real and imaginary components of the complex data. The resulting dataset was structured as 4D arrays of size (612×14×1×2N), where the third dimension (1) represents the single channel and the fourth dimension (2N) represents the real and imaginary parts for N (1024) samples. This preprocessing step was essential for compatibility with the CNN model, which interprets the input as a 2D image. The dataset was then partitioned into training (80%) and validation (20%) sets. A batch size of 32 was applied during training to optimize model learning and to periodically monitor performance through validation.

B. Convolutional Neural Network (CNN)

A CNN is a class of DL models designed to process grid-like datasets, such as images or higher-dimensional arrays [17]. CNNs achieve superior feature extraction with significantly fewer parameters than fully connected neural networks, making them computationally efficient.

TABLE I. SIMULATION PARAMETERS

Parameter	Value
Delay Profile	TDL-A, TDL-B, TDL-C, TDL-D, TDL-E
Delay Spread	1 - 1000 ns
Maximum Doppler Shift	1000 Hz
SNR	0 - 15 dB
Modulation	16 QAM
Antennas configuration	SISO (1×1)
Subcarriers	612
Symbols per slot	14
Resource Blocks	51
Subcarriers Per RB	12
Subcarrier Spacing	30 KHz
Transmission Direction	Downlink

Convolution operations enable CNNs to identify and leverage the structural patterns within these grids, making them effective for accurate and robust channel estimation.

The convolutional layers are the backbone of CNNs, consisting of multiple filters that slide across the input data to extract features such as edges, textures, and patterns. Each filter performs element-wise multiplications and summations over a local receptive field, producing feature maps. These feature maps indicate the presence of specific features across spatial locations, which are essential for accurate channel estimation. The convolution operation is defined as:

$$y(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x(i+m, j+n) \cdot k(m,n) \tag{6}$$

where y is the output feature map at position (i,j), x is the input image, M and N are the dimensions of the kernel.

The proposed CNN architecture in this research is designed to exploit the inherent spatial and temporal correlations within the time-frequency resource grid of communication systems. By treating resource grids as 2D images (where the vertical axis represents subcarriers, and the horizontal axis represents OFDM symbols), the channel estimation task is performed as an image processing, where convolutional operations predict the channel coefficients.

The proposed CNN architecture consists of an input layer that accepts the 612×14×1 time-frequency grid, followed by five convolutional layers. Layers 1 and 2 employ 9×9 kernels with 2 filters, layers 3 and 4 employ 5×5 kernels with 2 filters, and layer 5 employs a 5×5 kernel and 1 filter. All layers employ "same" padding to preserve the 612×14 spatial dimensions. Each convolutional layer is followed by a hyperbolic tangent (TanH) activation function, which enables the CNN model to learn nonlinear channel effects effectively. The final convolutional layer outputs a refined 612×14×1 channel estimate, matching the input dimension.

The training process was monitored using validation data, ensuring that the model generalizes well to unseen scenarios. Early stopping was implemented by terminating training when the validation loss ceased to improve, thus avoiding overfitting. See Table II, for the models hyperparameters.

To evaluate the model's performance, the MSE is utilized. It quantifies the average squared difference between the actual channel h_i and the estimated channel $\widehat{h_i}$, providing a robust measure of accuracy. The MSE is expressed as:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left(h_i - \widehat{h_i}\right)^2 \tag{7}$$

where N is the total number of samples.

TABLE II. CNN MODEL HYPER-PARAMETERS

Hyperparameter	Value
Number of Layers	5
Kernel Size	[9×9, 9×9, 5×5, 5×5, 5×5]
Filters	[2, 2, 2, 2, 1]
Batch Size	32
Learning Rate	0.0003
Epochs	200
Optimizer	Adam
Loss Function	MSE
Activation Function	TanH

IV. Simulation Results

This section presents the simulation results for the proposed CNN-based channel estimation compared to conventional (interpolation and LS) methods. The evaluation covers a range of scenarios, from mild to extreme conditions, including high Doppler shifts, severe multipath, and low SNR, to evaluate the model's performance and robustness.

A. Resource Grid Estimation

Fig. 2 illustrates the time-frequency resource grid, for the actual channel and the evaluated channel estimation techniques for visualization and comparison. This is an extreme scenario with multipath propagation and high mobility (considering FR3 band). It is characterized by an SNR of 10 dB, a delay spread of 200 ns, and a Doppler shift of 400 Hz. The actual channel represents the true channel coefficients, serving as the benchmark for evaluating the performance of the other methods. Variations along the x-axis indicate time-domain variations in the channel due to factors such as Doppler effects in high-mobility scenarios. In contrast, variations along the y-axis represent frequency-selective fading, due to multipath propagation.

The interpolation technique is relatively simple and computationally efficient. However, it fails to capture the full complexity and rapid variations of the channel, especially in highly dynamic scenarios, achieving the worst MSE of 0.19033. This can be seen from the visible discrepancies between the interpolated channel and the actual channel.

The conventional (LS) channel estimator minimizes the error between the actual and interpolated channel estimate. It achieves a better MSE of 0.15045 and yields a more accurate estimate than the interpolation technique. However, it also struggles to track time-domain channel variations due to high mobility scenarios as shown in Fig. 2.

The CNN-based channel estimator presents the best representation of the actual channel, with a 0.032453 MSE (78.42% improvement from LS). By treating the resource grids as 2D images, the CNN learns complex relationships between received signals and corresponding channel coefficients, effectively capturing variations in both time and frequency domains. This leads to improved robustness and accuracy compared to the other conventional techniques.

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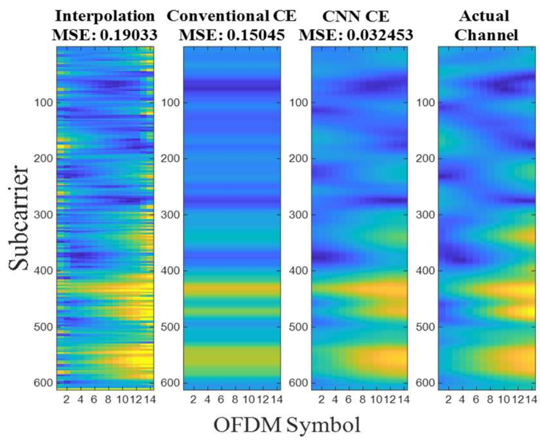

Fig. 2. Time-frequency resource grid of the different channel estimates

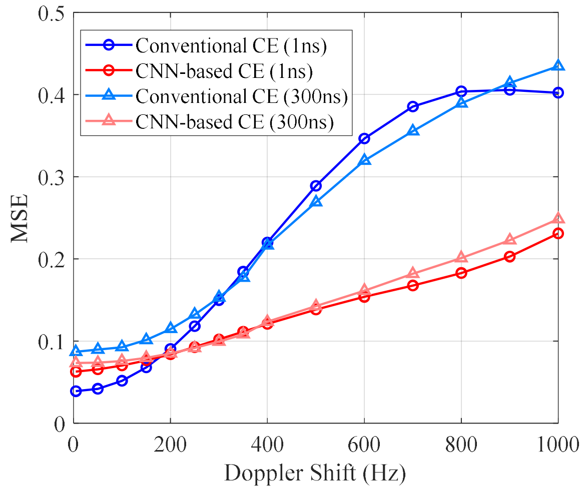

Fig. 3. MSE vs Doppler shift comparison at 0 dB SNR

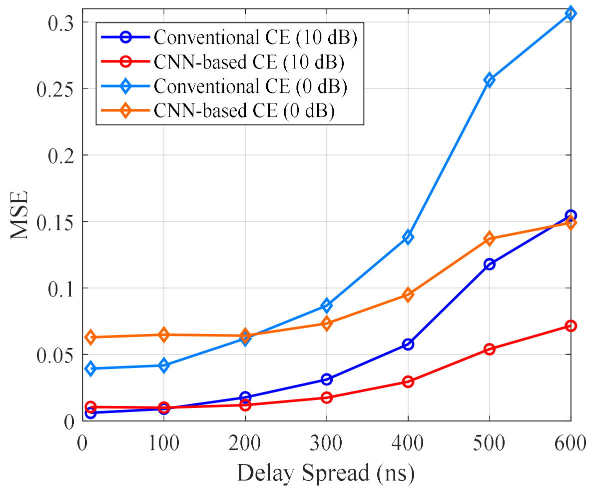

Fig. 4. MSE vs delay spread comparison at 0 and 10 dB SNR

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B. *Doppler Shift Performance*

Fig. 3 compares the MSE performance of the proposed CNN-based channel estimator with the conventional technique for Doppler shifts ranging from 5 Hz to 1000 Hz (low to high mobility). The results are presented for two delay spreads (1 ns and 300 ns) at 0 dB SNR (indicating a noisy scenario with the signal power equal to the noise power).

The MSE generally increases with higher Doppler shifts in both techniques, indicating that channel estimation becomes more challenging as the mobility of the transmitter or receiver increases. As the Doppler shift increases to 1000 Hz, the MSE for both conventional and CNN-based methods increase. This trend reflects the growing challenge of accurate channel estimation with increasing mobility, where the channel varies rapidly over time.

It can be observed that at lower Doppler shifts, the MSE performance of the CNN and the conventional technique is comparable. This is often the case because conventional methods are often sufficient when the channel is relatively static or slowly varying. However, the performance gap widens significantly as the Doppler shift exceeds 400 Hz. In other words, the CNN-based estimator outperforms the conventional estimator, particularly at higher Doppler shifts, which demonstrates the ability of the CNN to adapt to rapidly changing and high-mobility channels in extreme scenarios.

Both techniques exhibited a slight increase in MSE with the higher delay spread (300 ns). This is expected as larger delay spreads lead to more severe multipath fading. However, the CNN-based estimator demonstrated greater robustness to the increased delay spread, exhibiting a smaller increase in MSE compared to the conventional (LS) technique.

C. *Delay Spread Performance*

Fig. 4 compares the MSE performance of the proposed CNN-based estimator and conventional estimator under varying delay spread conditions at SNRs of 0 dB and 10 dB. Both methods show an increasing MSE trend as the delay spread increases. This reflects the challenging multipath propagation conditions at larger delay spreads. While the increase in MSE is significantly more pronounced for the Conventional method, especially at 0 dB SNR, the CNN-based estimator maintains significantly lower MSE compared to Conventional estimator, demonstrating its ability to handle severe noise and multipath fading conditions effectively.

It is observed that at lower delay spreads (< 200 ns), the conventional technique achieves performance comparable to that of the CNN model. However, as the delay spread increases (> 400 ns), the performance gap between both techniques widens and the conventional technique degrades significantly, while the CNN-based estimator maintains a more robust performance, emphasizing the strength of the CNN-based approach in extreme scenarios.

D. *SNR Performance*

Fig. 5 shows the MSE performance of the CNN-based estimator and conventional (LS) estimator from 0 to 25 dB SNR. As the SNR increases, the MSE decreases for both techniques, indicating improved channel estimation accuracy in higher SNRs. This behaviour aligns with theoretical expectations, as higher SNR typically results in less noise interference during channel estimation.

At higher SNR values (> 15 dB), the MSE performance of both techniques converges, achieving near-identical low error rates. This indicates that under low-noise conditions and high SNR, conventional methods can match the performance of CNN-based methods. This convergence is likely because the CNN was trained only on data within the 0–15 dB SNR range, which limits its ability to generalize to higher SNR values. Expanding the training dataset to include higher SNR values could potentially improve the CNN's performance in such scenarios.

However, at low SNR values (0–10 dB), the CNN-based channel estimator demonstrates a significantly lower MSE compared to the conventional channel estimation technique,

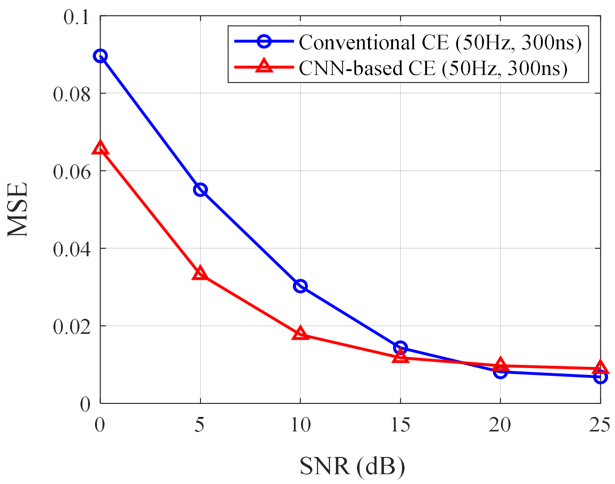

Fig. 5. MSE vs SNR comparison at 50 Hz and 300 ns

showcasing its ability to handle noisy conditions better. This highlights the robustness of CNN-based models in extreme scenarios with high signal degradation and noise levels.

E. Complexity Analysis

The Big O notation is crucial for understanding algorithm efficiency and computational complexity. The LS estimation involves matrix inversion with a complexity of approximately $O(N^3)$, where N is the number of subcarriers or channel taps. For M symbols, the total complexity scales as $O(MN^3)$. The LS is relatively less complex, and ideal for real-time applications under simpler channel conditions. However, it becomes impractical for larger N, and struggles to cope with non-linearities and noise, making it unsuitable in extreme scenarios.

The computational complexity of CNN during training is approximately $O(NDF^2C)$, where N is the number of samples, D is the depth of the network, F is the filter size, and C is the number of channels. The training phase requires substantial computational resources and time. However, during deployment, the computational complexity reduces, focusing on matrix multiplications and activation functions. Making the CNN model suitable for real-time applications.

V. Conclusion

This research has provided a comprehensive investigation into the performance of the CNN-based channel estimation model in comparison with conventional channel estimation in extreme scenarios in 6G and beyond. The study evaluated both methods under varying Doppler shift, delay spread, and SNR, demonstrating the efficacy and robustness of the CNN-based channel estimator in challenging scenarios.

The CNN-based channel estimator exhibited remarkable resilience to extreme scenarios, maintaining lower MSE even under high Doppler shifts, significant delay spreads, and noisy channels. In contrast, conventional channel estimation techniques suffered significant performance degradation under the same conditions, highlighting their limitations in extreme scenarios. The CNN model is also computationally efficient during deployment, making it feasible for real-time applications.

These findings highlight the superior performance of the CNN-based channel estimator as a robust solution for reliable communication in 6G. Future work will investigate alternative DL models to further enhance channel estimation.

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