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A Unified DNN-Based Channel Estimator For Massive MIMO Systems Under Various 5G Channel Scenarios

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***Abstract:** An accurate channel estimate is crucial for 5G and future wireless communications to achieve the performance gains offered by Massive MIMO systems. When dealing with less-than-ideal propagation conditions, standard estimation approaches such as Least Squares (LS) and Minimum Mean Square Error (MMSE) might be problematic in real-world deployment scenarios. In this paper, a unified model for channel estimation using Deep Neural Networks (DNNs) is presented. This model shows good performance in many real-world channel scenarios, including pilot contamination, time-varying channels, OFDM-based frequency-selective fading, spatially correlated MIMO channels, Rayleigh fading, and environments polluted by impulsive non-Gaussian noise. We model and evaluate the DNN's performance in comparison to LS and MMSE estimators, with normalized mean squared error (NMSE) serving as the primary metric. The findings show that the proposed DNN consistently outperforms traditional methods, with an NMSE improvement of up to 6 dB in challenging scenarios such as impulsive noise and pilot contamination. Another aspect of the DNN that proves its adaptability and durability is its strong generalization across different channel types and SNR levels. With only one DNN architecture trained on a diverse dataset encompassing all six channel conditions, scenario-specific estimators are unnecessary. Among the many feasible and scalable options for deployment in varied 5G networks, this research demonstrates that a unified DNN-based channel estimator may provide low inference latency and high estimate accuracy. This study's findings support the future use of data-driven approaches to communication system design, particularly in contexts where analytical modelling fails to provide satisfactory results.*

***Keywords:** Channel Estimation, Massive MIMO, 5G Networks, Deep Neural Networks, Normalized Mean Square Error*

1. INTRODUCTION

A new evolutionary age in wireless communication has begun with the fast development of 5G technology, which has prompted the need for innovative solutions to meet the increasing needs for faster data rates, more reliable connections, and better use of spectrum [1]. Enhanced mobile broadband, enormous machine-type communications, and ultra-reliable low-latency communications are some of the uses for 5G networks, but meeting complex performance requirements while improving user connection is no easy task [2]. The use of MIMO systems, which dramatically improve data throughput and network stability by using multiple antenna components, is a crucial component in addressing these difficulties [3].

Multiple-input, multiple-output (MIMO) technology allows for the simultaneous broadcast of many data streams over a single wireless channel by using spatial diversity and a multiplexing approach. In situations when demand is strong, this characteristic is crucial since conventional methods might fail to maintain efficiency and performance because of increased interference and fading effects. Conventional approaches have limitations in computing complexity and flexibility when dealing with variable channel circumstances, particularly in high-order modulation situations, notwithstanding the advantages of MIMO systems [4]. Increased bandwidth and spectral efficiency are benefits of the wireless system that result from the installation of over a hundred antennas at the base station. Massive MIMO is a system that outperforms the traditional MIMO system in terms of user

capacity. Acquiring precise channel status information (CSI) for each communication device, however, is the primary obstacle to expanding the number of antennas. Estimating the channel characteristics requires the precise CSI. Pilot contamination, the channel's time-varying nature, and spatial correlation all contribute to the difficulty of channel estimation in Massive MIMO systems.
The channel estimation for the conventional wireless communication system uses the Least Square (LS) estimation or Minimum Mean Square Error estimation methods due to their simplicity and effectiveness. These two techniques are frequently used because LS estimation does not require any prior knowledge of channel statistics. But a time-varying channel or a channel accessed by multiple users creates heavy interference, which reduces the Signal-to-Noise (SNR) ratio and consequently deteriorates the performance of the LS estimator. Alongside the MMSE channel estimation technique, which offers better accuracy, there is an increase in computational complexity.
The problems associated with channel estimation in Massive MIMO systems can be addressed by advancements in datadriven techniques, particularly when applied in wireless communication and signal processing, such as Deep Neural Networks (DNN) [5]. The DNN models can be trained according to the channel scenarios whose characteristics are already known to the receiver, and the trained model can predict the alternate channel characteristics based on the received information bits [6].
This paper proposes a unified DNN model to determine the channel characteristics and the model performance is compared with the other traditional models. The model is tested over five different channel scenarios applicable for 5G wireless communication system. The proposed model is tested over different channel scenarios affected by pilot contamination, a channel that has a time-varying nature, OFDM based multipath channel, a Rayleigh fading scenario which considers non-line of sight components and lastly a non-gaussian noisy channel. The performance of the proposed model is evaluated for normalised mean square (NMSE) error versus the signal to noise ratio (SNR) and compared with the traditional LS and MMSE approaches used for channel estimation. The unified DNN model is trained for its implementation in real time scenarios for a channel having a complex nature.

2. LITERATURE REVIEW

The efficiency and capacity requirements for fifth-generation (5G) communications networks and subsequent generations depend on Massive MIMO systems, which represent an evolutionary step in mobile data transmission [7]. These systems significantly enhance bandwidth, power savings, and link reliability by using an array of antennas at the base station to offer services to multiple users. The precision of Channel State Information (CSI), which directly influences precoding, detection, and system throughput, is essential for realizing the benefits of massive MIMO.
However, the channel estimation for a Massive MIMO system at the receiver side faces various challenges due to the utilization of large number of antennas. The estimation of channel using tradition methods by every individual user is not practically feasible because the utilization of large number of antennas at the transmitter yields uncountable number of channel coefficients [8]. Alongside the known pilot used for channel prediction will encounter contamination due to the repeated combinations of pilot sequences used in the neighbouring cells. The large number of antenna system utilizes redundant pilot sequences and these pilot sequences also interferes with the information consisting known pilots used for the other users located in the neighbouring cells. The time varying nature of the channel is associated with the mobile users. The fast mobility of the user will encounter the frequent change in the channel characteristics which will subsequently degrades the performance of the convention channel estimation methods because these methods only work in the static or low mobility scenarios [9]. Moreover, the multipath propagation system encounters the frequency selective fading for each transmitted path making the channel estimation more complicated. Thus, the correct analysis of the channel characteristics becomes the primary objective of the 5G and the future 6G wireless communication system to attain their maximum efficiency [10]. Hence, to identify the best suitable channel estimation methods for the massive MIMO system, the previous research studies are reviewed and analyzed here.
The previous research study shows that the Deep neural network is a data-driven network model, which belongs to the field of artificial intelligence and machine learning. The DNN model can easily address complex channel characteristics by training and mapping it to forecast unknown channel characteristics, without requiring prior knowledge about them. In [11], the author used a Convolutional Neural Network (CNN) model to predict the

nature of a multipath propagation transmission that follows an OFDM multicarrier transmission scheme, and the transmitted bits undergo a frequency selective fading scenario. The CNN model performed extremely well for the AWGN channel and also for the non-Gaussian noisy channel. The model shows superior performance over the other conventional channel estimation techniques. In [12], the author trained a DNN model for predicting the channel characteristics, where the bits were transmitted using an OFDM transmission scheme. The DNN model outperformed the other conventional methods. The performance was evaluated between NMSE versus the different values of SNR.

In [13], the author used various machine learning models to estimate the channel for a MIMO-OFDM transmission system. In this study, the authors used different supervised learning schemes to evaluate the channel characteristics. The available data sets were used to model time-varying channel characteristics. In [14], the author proposed a hybrid model comprising a Harris optimizer and a Deep Learning Neural Network model to analyze the channel characteristics of a multi-user Massive-MIMO transmission system. In [15], the author used a DNN model for a 6G wireless network. The Reinforcement learning model was trained to work over the physical layer of the 6G network.

In [16], the author used the CNN model to estimate the performance of a time-varying OFDM channel model, where the signal was transmitted in the orthogonal bit streams following a multipath. The CNN model was trained to identify the channel and also to denoise the transmitted signal. The model had better accuracy than the other model without requiring any additional training. Moreover, in [17], the author proposed a hybrid DNN model to perform channel estimation even with hardware impairment. The model was trained for a MIMO system that produces a hybrid beamforming in a real-time scenario.

In [18], the author presents an intelligent reflecting surface-assisted multi-user communication system that the author has developed. The system models channel estimation as a denoising problem and uses a deep residual learning technique to recover the channel coefficients from pilot-based observations that are noisy by implicitly learning the residual noise. In [19], the author integrates the benefits of classical and deep learning approaches by using typical pilot-based channel estimates as a prior inside the deep learning framework. Furthermore, they used a Monte Carlo model to derive uncertainty-aware predictions for augmenting the model's security and reliability. The suggested method surpasses conventional and deep learning-based systems in terms of security, trustworthiness, and performance in self-driving cars and for augmented reality.

In both low and high SNR regimes, DL-based estimators frequently outperformed iterative methods, particularly when trained on noisy and distorted channel environments, according to a comparative study in [20]. Their research also highlighted how trained neural networks' reduced inference latency may be used in real-time. Although simulation-based assessments show promise, there are other factors to take into account when using deep learning-based channel estimators in the real world. These consist of hardware compatibility, inference delay, and model size. Research on edge deployment with effective models (e.g., by knowledge distillation, quantization, or pruning) is ongoing. Although federated learning and online learning are promising alternatives, real-time training or adaptation is still a bottleneck. For validation and standardization, integration with 5G testbeds and software-defined radio platforms (like USRP) is being investigated. At last, the conventional estimators such as LS and MMSE remain fundamental, although they encounter issues with scalability and performance in large MIMO systems. Deep learning-based techniques, especially those that use CNNs and DNNs, have become strong substitutes that can generalize across different channel conditions, adjust to changes in real time, and get beyond drawbacks like noise and pilot contamination. The research trajectory indicates more hybrid, intelligent, and efficient channel estimate methods designed for next-generation wireless networks, even if there are still practical implementation obstacles. Therefore, the most efficient method to estimate the channel characteristics is investigated in this paper. The performance comparison of the traditional estimation methods with our unified DNN model for all six channel scenarios is evaluated in this paper.

3. MATERIALS AND METHODS

A single-cell massive MIMO uplink system with K single-antenna user terminals and M antennas at the base station (BS) is being considered. The received pilot signal $Y_p \in \mathbb{C}^{M\,X\,\tau p}$ at the BS is modelled as:

$$Y_P = H\varphi^T + N \qquad (1)$$

where $H \in \mathbb{C}^{M\,X\,K}$ is the complex channel matrix, $\varphi \in \mathbb{C}^{K\,X\,\tau p}$ is the pilot matrix, and N is the additive white Gaussian noise matrix.

3.1 Channel Estimation Techniques

In wireless communication systems, channel estimation is a crucial element, particularly in Massive MIMO and 5G contexts, where precise wireless channel information is essential for achieving spectral efficiency, effective beamforming, and reliable signal identification. The two main categories of channel estimation approaches are machine learning (data-driven) and classical (model-driven).

Least Squares (LS): The pilot matrix is pseudo-inverted to calculate the LS estimator:

$$\widehat{\boldsymbol{H}}_{\boldsymbol{LS}} = \boldsymbol{Y_P}\left(\boldsymbol{\varphi^T}\right) \quad (2)$$

LS estimation is vulnerable to noise and pilot contamination, particularly in low SNR or overloaded massive MIMO settings, while being computationally inexpensive and without requiring previous channel data.

Minimum Mean Square Error (MMSE): The MMSE estimator, assuming the noise variance σ2 and the channel covariance matrix R, is as follows:

$$\widehat{\boldsymbol{H}}_{\boldsymbol{MMSE}} = \boldsymbol{R\varphi}\,(\boldsymbol{\varphi^H R\varphi} + \boldsymbol{\sigma^2 I})^{-\boldsymbol{1}}\boldsymbol{Y_p} \quad (3)$$

Through the use of previous statistical information about the channel and noise, the MMSE estimator enhances the Least Squares (LS) method. In particular, it makes use of the second-order statistics of the channel and noise to minimize the mean squared error between the real and estimated channel.

Deep Neural Network (DNN): The DNN-based estimator models the intricate, nonlinear connection between the underlying wireless channel and the incoming pilot signals by using supervised learning. The DNN learns to approximate the mapping directly from data, in contrast to conventional LS and MMSE techniques, which depend on linear algebra or second-order statistics. This enables the potential to record higher-order interactions and demonstrates resilience to various limitations. A fully connected feed-forward neural network was developed using supervised learning [21]. The attributes of the input are the real and imaginary parts of the acquired pilot matrix, and the outcome is the anticipated channel matrix. Rayleigh fading data with additive noise was used for training, and it was then evaluated in a variety of channel scenarios.

3.2 Variations in the Channel Characteristics

The success of Massive MIMO systems depends heavily on accurate channel estimates, especially in the uplink when base stations must deduce user channels from pilot signals. Because of their tractability and ease of analysis, the Least
Squares (LS) and Minimum Mean Square Error (MMSE) estimators have historically been used as standards. Nevertheless, these techniques often fail in less-than-ideal situations, including non-Gaussian noise, pilot contamination, and spatial correlation.

Data-driven channel estimation techniques have become more popular as a result of recent developments in deep learning (DL). Nonlinear mappings and statistical patterns that are missed by conventional estimators may be learnt by DL models [22]. Here, we examine the most pertinent issues and the ways in which DL methods, in particular unified deep neural networks (DNNs), have shown potential for resolving them.

a) Baseline Rayleigh Fading

The Rayleigh fading model produces independent and identically distributed (i.i.d.) complex Gaussian channels under the assumption of a rich scattering environment devoid of line-of-sight (LOS). Since LS and MMSE estimators do rather well in this baseline situation, deep learning models—like CNNs—are often trained on it before being applied to more complicated ones. [23, 24].

b) Correlated Channels for MIMO

Antenna elements in real-world systems exhibit spatial correlation, particularly in mm Wave and compact array topologies. Although MMSE estimation may theoretically handle correlation, it requires precise information about the channel covariance matrices, which is often inaccessible or imprecise. However, DL models may outperform traditional techniques in coupled channels and implicitly learn spatial patterns from data. [25, 26].

c) Contamination of Pilots

A major drawback of TDD huge MIMO systems is pilot contamination, which results from the reuse of pilot sequences in neighbouring cells. Because LS estimators are unable to discriminate between users sharing the same pilot who are in-cell and those who are out-of-cell, they are especially susceptible. This is somewhat improved by MMSE when interference is known beforehand. By learning to distinguish between overlapping pilot structures, DL models have been shown to have strong denoising capabilities [27, 28].

d) Time-varying channel based on mobility

Instantaneous estimation is inadequate for high-mobility users because they cause Doppler shifts and temporal fluctuation in the channel. Outperforming snapshot-based estimators, recurrent neural networks (RNNs), particularly gated versions (GRUs or LSTMs), have shown great performance in capturing temporal relationships [29, 30].

e) OFDM Multipath, or frequency-selective channels

Wideband communication in 5G systems causes channels to become frequency selective, and multipath delay profiles are used to simulate them. Frequency-domain correlation is ignored while estimating these channels on a per-subcarrier basis. Superior performance may be achieved by combining 2D CNNs with attention methods to concurrently utilize spatial and spectral characteristics [31].

f) Impulsive Non-Gaussian Noise

Urban, automotive, and industrial settings often experience heavy-tailed or impulsive interference, which goes against the MMSE/LS Gaussian noise assumption. DNNs outperform classical estimators, which lack this flexibility, when trained on data tainted by impulsive noise because they become resilient to outliers [32-34].

4. RESULTS AND DISCUSSIONS

The performance of the suggested unified DNN model, LS, and MMSE in each of the six channel situations is assessed to evaluate their efficacy. Convolutional and recurrent layers are used in the DNN model to manage temporal, frequency, and spatial fluctuations. To guarantee generalization, it is trained collaboratively on all six cases while maintaining scenario balance. The following Massive MIMO system parameters are assumed in all simulations:

Table 1. Value of different parameters used in the simulation

Parameter	Value
Antennas (BS)	64
Users (UE)	8
OFDM Subcarriers	128
Pilot Length	8 symbols
Modulation	QPSK
SNR Range	0–30 dB
Dataset Size	10,000 samples per scenario

The main statistic is the Normalized Mean Squared Error (NMSE), and a lower NMSE indicates a better channel estimate.

$$NMSE = E\left[\frac{\|\hat{H}-H\|_F^2}{\|H\|_F^2}\right] \quad (4)$$

The suggested unified Deep Neural Network (DNN)-based channel estimation framework is thoroughly evaluated in this part and contrasted with conventional LS and MMSE estimators. The Normalized Mean Squared Error (NMSE) measure is used to assess effectiveness for six actual 5G channel instances: pilot contamination, OFDM multipath fading, correlated MIMO, Rayleigh fading, time-varying channels, and impulsive noise. Simulations are conducted across a spectrum of signal-to-noise ratios (SNRs) ranging from 0 to 30 dB, with results averaged over numerous Monte Carlo trials as shown in Fig 1.

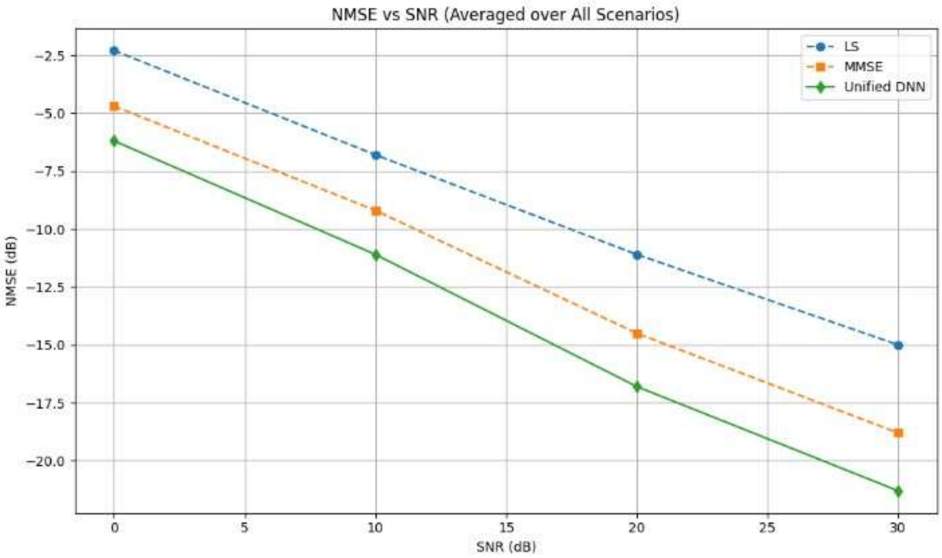

Fig. 1: Performance of estimators based on LS, MMSE, and DNN over many Monte Carlo simulations

Table 2 shows the baseline scenario with channels replicated as i.i.d. Rayleigh fading; the deep neural network demonstrates superior performance compared to both least squares and minimum mean square error methods across all signal-to-noise ratios. At 30 dB, the DNN attains an NMSE of approximately −21 dB, in contrast to −18.6 dB for MMSE and −14.8 dB for LS. This demonstrates the DNN's ability to learn effective channel mappings from noisy observations, even under idealized conditions. Channel correlation diminishes the efficacy of LS and MMSE methods by decreasing spatial diversity and introducing non-orthogonality among channel vectors. The DNN exhibits robustness in this context, achieving an NMSE enhancement exceeding 3 dB relative to MMSE at elevated SNRs. This indicates that the DNN effectively captures spatial dependencies overlooked by traditional linear estimators.

Table 2. NMSE vs. SNR (Averaged over all scenarios)

SNR (dB)	LS NMSE	MMSE NMSE	Unified DNN NMSE
0	-2.3 dB	-4.7 dB	**-6.2 dB**
10	-6.8 dB	-9.2 dB	**-11.1 dB**
20	-11.1 dB	-14.5 dB	**-16.8 dB**
30	-15.0 dB	-18.8 dB	**-21.3 dB**

In the next scenario, Pilot contamination leads to severe performance degradation for LS and MMSE due to interference from users in neighbouring cells using the same pilot sequences. The DNN estimator significantly mitigates this issue, improving NMSE by 4–5 dB over MMSE at 30 dB SNR. The performance gain stems from the DNN’s ability to learn implicit interference suppression mechanisms during training. In high-mobility scenarios, time variation in channel coefficients introduces challenges in tracking accurate channel state information. The proposed DNN model shows enhanced robustness by capturing temporal dynamics, outperforming LS and MMSE by up to 4 dB, as shown in Fig 2. Unlike MMSE, which relies on static channel assumptions, the DNN can generalize over dynamic temporal patterns learned during training. The OFDM-based massive MIMO systems face frequency-selective fading across subcarriers. Here, the DNN again outperforms traditional estimators, demonstrating an improvement of up to 5 dB in NMSE over MMSE. The gain can be attributed to the DNN’s ability to exploit cross-subcarrier correlations and multipath features jointly,

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unlike LS/MMSE, which treat each subcarrier independently. In environments characterized by impulsive, non-Gaussian noise, LS and MMSE suffer due to their reliance on Gaussian noise assumptions. The DNN, trained on a mix of Gaussian and impulsive noise distributions, exhibits higher resilience, achieving 3–6 dB better NMSE performance across the SNR range. This highlights the DNN's flexibility in handling non-ideal noise characteristics through data-driven learning. Lastly, A major contribution of this work is the demonstration that a single, unified DNN model can generalize effectively across all channel scenarios. This eliminates the need for scenario-specific estimators, significantly simplifying deployment in heterogeneous environments. The model's ability to learn abstract representations that span temporal, spectral, and spatial dimensions makes it especially suited for future 5G/6G networks characterized by environmental variability and user mobility.

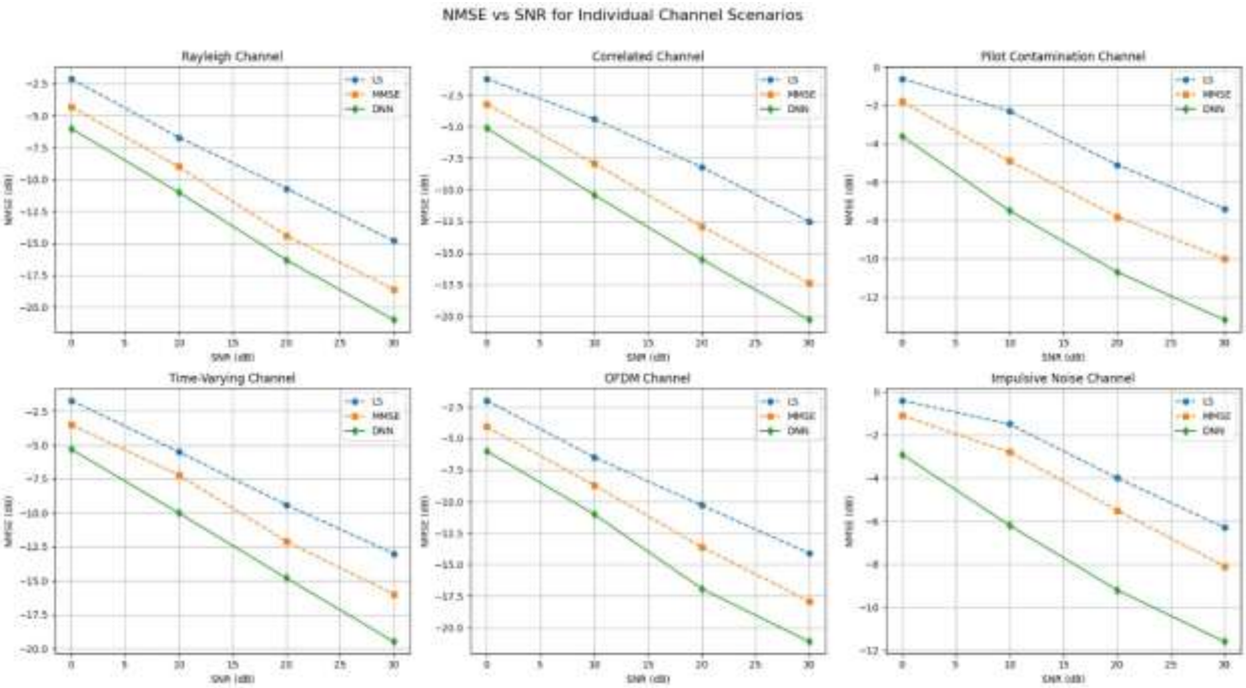

Fig. 2: Analysis of LS, MMSE, and DNN-based channel estimates in six distinct channel scenarios.

5. CONCLUSIONS

A significant finding is that a single, cohesive DNN model trained on all kinds of channels functioned rather well in every situation. Multiple scenario-specific estimators are no longer required, and real-time flexibility is made possible—a crucial feature for 5G and future systems that function in very diverse contexts. The DNN model's strong generalization ability is confirmed by its constant performance over a broad variety of channels. This is likely due to its nonlinear mapping capabilities and implicit modelling of both spatial and temporal dependencies.

In a massive MIMO uplink system, this work assessed the effectiveness of LS, MMSE, and DNN-based channel estimation approaches under various practical 5G channel circumstances. LS is computationally straightforward; however, it is not robust. Although MMSE provides better accuracy, its reliance on previous data limits its use. On the other hand, the suggested DNN estimator performs noticeably better in all channel models, including those with correlated, time varying, and nonlinear circumstances. These results demonstrate how well deep learning works to solve real-world channel estimation problems. Future research may focus on incorporating attention processes, refining the DNN for real-time processing, and validating the methodology using actual 5G datasets.

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