E-ISSN: 2583-9667
Indexed Journal
Peer Reviewed Journal
https://multiresearchjournal.theviews.in

Received: 25-04-2025
Accepted: 30-05-2025
Published: 14-07-2025

INTERNATIONAL JOURNAL OF ADVANCE RESEARCH IN MULTIDISCIPLINARY

Volume 3; Issue 3; 2025; Page No. 338-343

Efficient Deep Learning for Massive Mimo Channel State Estimation

[1]Anubhav Pandey and [2]Dr. Vinod Kumar Suman

[1]Research Scholar, Department of Electronic and Communication, Mahakaushal University, Jabalpur, Madhya Pradesh, India
[2]Associate Professor, Department of Electronic and Communication, Mahakaushal University, Jabalpur, Madhya Pradesh, India

DOI: https://doi.org/10.5281/zenodo.18265463

Corresponding Author: Anubhav Pandey

Abstract

Future wireless communications networks with the aid of the massive MIMO technologies will be able to significantly enhance the spectrum efficiency. This will be made possible because a base station (BS) that will have numerous antennas. can service many users' equipment (UE) terminals. Evidence from information theory suggests that such multiantenna arrays allow for high-capacity communications using beamforming. Massive MIMO networks can't perform as intended without precise predictions of the downlink channel state information (CSI) in the trans-matter to precoding, which is required by the base station. Receivers can usually estimate CSI with the use of known pilot signals. The BS is able to measure the down-link CSI using pilots in uplink broadcasts in the special case of time-division duplex (TDD) mode, courtesy of channel reciprocity. The BS uses UE feedback to approximate downlink CSI in frequency division duplex (FDD) mode because the channel reciprocity of the uplink channel and the downlink channel is less than 100 rather limited. One important consideration is how to reduce feedback bandwidth while keeping downlink CSI predictions correct; this is known as the CSI feedback scheme. We demonstrate that this approach may reduce computing complexity while preserving similar estimate accuracy.

Keywords: Deep Learning, MIMO, networks, communications and technologies

1. Introduction

Historically, there have been three primary approaches to massive MIMO channel estimation: blind, semi-blind, and pilot-based. By recreating the channel response with the use of a priori channel information, one of these approaches, pilot-based channel estimation, enhances accuracy and dependability. Extensive investigation and usage of this approach have been conducted by scientists. Many pilot-based channel estimate methods use either least square (LS) or minimum mean square error (MMSE). An LS channel estimation feature that stands out technique is its reduced computational cost. But it ignores the impact of background noise. In real-world settings, it is especially vulnerable to noise amplification since it depends on the discrepancy between actual and estimated data. When the channel goes through widespread fading, which drastically reduces the precision of channel estimate, this vulnerability becomes much more apparent. Researchers have suggested the MMSE channel estimation method as a solution to the problems with the LS algorithm. The optimization target of this approach is the computed as the direct usage of the difference between the estimator's actual and estimated values.

Significant advancements the rapid increase in computing power has enabled advancements in artificial intelligence, particularly in deep learning (DL) technologies. Emerging from these advancements have been revolutionary breakthroughs in several domains, including computer vision, natural language processing, and voice signal processing. This has prompted some academics to investigate potential AI-based wireless communication system integrations, with the goal of creating smart wireless communication systems that complement existing wireless communication infrastructure and lead to ground-breaking innovations in the industry. In addition, by optimizing spatial resources via the use of an ultra-high antenna arrangement, massive MIMO technology greatly increases the capacity of communication networks. This development also produces massive amounts of data via wireless transmission, which is crucial for the implementation of AI in this field.

Massive MIMO differs from traditional MIMO in that it uses a single RF chain for all of its antennas, which increases the complexity of the gear and the amount of power it consumes. Antenna selection is carried out according to signal strength, magnitude, and area of acceptance (AoA), which decreases the quantity of RF chains and so addresses these issues. The goal of digital beamforming in a hybrid structure is to achieve multiplexing advantages, whereas the goal of analog beamforming, which makes use of phase shifters, is to achieve directionality gains. Their solution was to create a hybrid beamformer. In this case, the network performance is enhanced by integrating the digital combiner and precoder that work with analog. Prior work has built coupled precoders and combiners using a Convolutional Neural Network (CNN), which enhances spectrum efficiency. With the increasing demands placed on wireless communication networks for both capacity and coverage, the use of multiple-input multiple-output (MIMO) technology has become more important in recent times. the acronym for "multi-input multiple-output" technology uses a network of several antennas, one for sending data and one for receiving it.

2. Literature Review

Chun, Chang-Jae *et al*. (2019) [1]. For the massive MIMO system, we provide a channel estimate deep learning (DL) based approach. In contrast to other studies, we provide a channel estimation technique for the case when the quantity of transmit antennas is smaller than the pilot length. The suggested method employs DL for pilot-aided and data-aided channel estimation in a two-stage approach for estimate. Using a DNN and a two-layer neural network is the first stage. (TNN) to simultaneously create the channel estimator and the pilot. Step two involves iteratively using a second DNN to further improve channel estimate accuracy. The simulation results show that compared to the usual channel estimation technique, the suggested system does far better. We also learn the optimal pilot length from the number of transmit antennas, which is a useful insight.

Khunteta, Shubham *et al*. (2022) [2]. Health, security, and user monitoring are just a few of the many areas that have made indoor localization using wireless systems a hotspot for study in recent years. Although a Global location System (GPS) is ideal for outside localization, it does not provide precise location when used inside. One prominent approach to the indoor localization issue is Wi-Fi fingerprinting, which uses the received signal strength from numerous access points. An essential study field towards 6G, Integrated Communication And Sensing (ISAC) refers to the fact that sensing has also become practical alongside communication as wireless networks progress towards higher frequencies, larger bandwidth, and a wider antenna array. ISAC uses estimated sensing parameters, such as fine-range, Doppler, and angular data that includes the object signature, to navigate. Understanding the sensor parameters is the key to fixing a localization issue. In this study, we provide an approach to indoor localization for IEEE 802.11ay WLAN networks that makes use of signal processing and ML.

Lu, Shuyu. (2024) [3]. An important metric for gauging A fundamental aspect of wireless communication is channel estimation, which impacts system performance. Recent discussions in the field of wireless communication machine learning application research have focused on methods that combine deep learning with channel estimation. Massive MIMO and other wireless communication technologies make it impossible to use traditional channel estimate methods due to their high cost and lack of precision. Channel estimation for big MIMO systems utilizing a combination of deep neural networks (DDN) is the subject of this study. and the least squares' technique. While simulating for the same analog channel, the results show a much lower loss function compared to standard techniques like LS or the lowest mean-square error approach. Efficiently addressing the issue of lack of accuracy and considerably improving performance may demonstrate that the channel estimator's design is adequate.

Khan, Inaamullah *et al*. (2023) [5]. A difficult issue in MIMO-OFDM wireless systems estimates wireless channels. The capacity and performance of wireless networks are enhanced by MIMO-OFDM because it makes use of the available space. Coherent signal identification in receivers depends on perfect Channel State Information (CSI), hence an accurate channel estimation is critical to the performance of these systems. Hence, wireless channel estimate is essential for OFDM systems to operate. We provide a technique for MIMO-OFDM networks that estimates channels by merging pilot symbols with reliable data symbols in this research. Spectral efficiency is enhanced and virtual pilots are provided by trustworthy data symbols. By eliminating the requirement for any additional resources, such as an excessive number of training symbols, the proposed Data Aided Channel Estimation (DACE) technique achieves the goal performance. In terms of Mean Square Error (MSE) and Bit Error Rate (BER), it outperforms the previous methods of channel estimation that relied on Least Square (LS) and Linear Minimum Mean Square Error (LMSSE).

Adenekan, Tobiloba. (2024) [6]. IRS Optimization in IoT-Driven MIMO Communication with the use of Machine Learning Models Driven by AI. By facilitating connection between a multitude of objects, the Internet of Things (IoT) is revolutionizing communication infrastructures. More efficient, scalable, and dependable communication solutions are in high demand due to the expansion of IoT networks. The foundation of contemporary wireless communication, Variety of Input The capacity of channels is expanded and data rates are rapid using Multiple-Output (MIMO) technology. By enhancing signal quality, increasing energy efficiency, and decreasing interference, Intelligent Reflecting Surfaces (IRS) have the potential to completely transform their utilization. Improving IRS in MIMO communication networks powered by the IoT is the subject of this article by integrating AI and ML models. We talk about how AI and ML may improve channel estimates, automate real-time network optimization, and allow intelligent IRS element setup.

3. Research Methodology

3.1 Deep Learning for CSI Estimation

Important topics of using deep learning to MIMO CSI estimation will be covered in this chapter. For the purpose of CSI estimation, we provide a concise introduction to key ideas in deep learning. Deep learning-based CSI estimate has been made possible via the use of data pre-processing methods and domain knowledge applications. In this paper, we provide spherical normalization, a CSI pre-processing approach that we believe may improve estimate accuracy while keeping the computing cost of existing estimation algorithms relatively constant.

3.2 Data Pre-processing for CSI Data
Appropriate data Prior to training a model, pre-processing entails changing the input data in a certain sequence, which is essential for machine learning tasks. Machine learning relies on consistent scales for input features, which can only be achieved by data pre-processing. Here we will examine the authors' crucial pre-processing choices that were derived from their expertise in MIMO CSI. data, specifically at domain transformations, truncation, and normalization, three crucial pre-processing approaches in deep learning for CSI estimation.

3.3 Spherical Normalization
Csi Net-Pro, our optimized network design, and our work in spherical normalization are discussed here.
We suggest spherical normalization as an alternative to When applied to very sparse CSI data, minmax normalization yields a low variance distribution. Think about z-score normalization before we go into a detailed description of spherical normalization. Suppose we have a normally distributed random variable x. This random variable's z-score normalized version is provided as

$$z = \frac{x - \mu}{\sigma}.$$

3.4 CsiNet-Pro
Introducing CsiNet-Pro, a network designed with bigger convolutional kernels and eliminated residual connections. When compared to smaller kernels, such as in CsiNet, bigger kernels, such as in CsiNet-Pro, enable the network to collect characteristics that correlate to wider delay spreads. From r to $r + 1$, Given that the encoder must feedback both the compressed feedback from the autoencoder and the power of the CSI matrix, kHk, the number of floating-point elements that must be given back increases. The CsiNet-Pro architecture, here referred to as "SphNet," employs spherical normalization, as seen in Figure 1.'

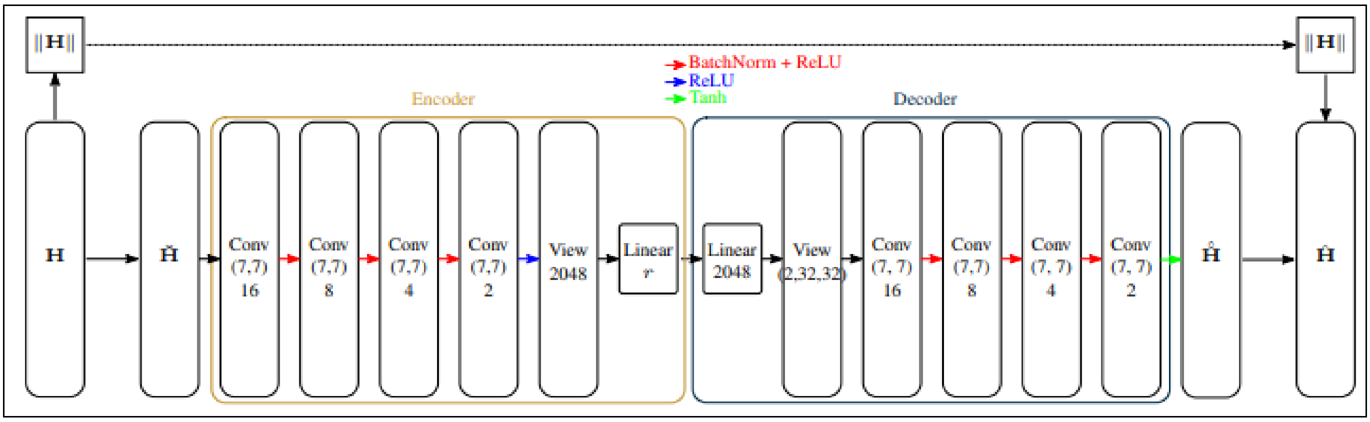


Fig 1: We use Spherical Normalization in our CsiNet-Pro architecture to create SphNet.

3.5 Temporal Coherence and Differential Encoding
Here we analyse ways to take advantage of the time connection between CSI of succeeding timeslots. The greatest amount of time that an estimate of the channel's SNR may be used before it goes below a specific threshold is called the channel's coherence time. As seen in Figure 2 for this time interval (t = ti 1), the connection between cells in CSI Hi and Hi 1 is relevant. the sake of illustration, is rather high.

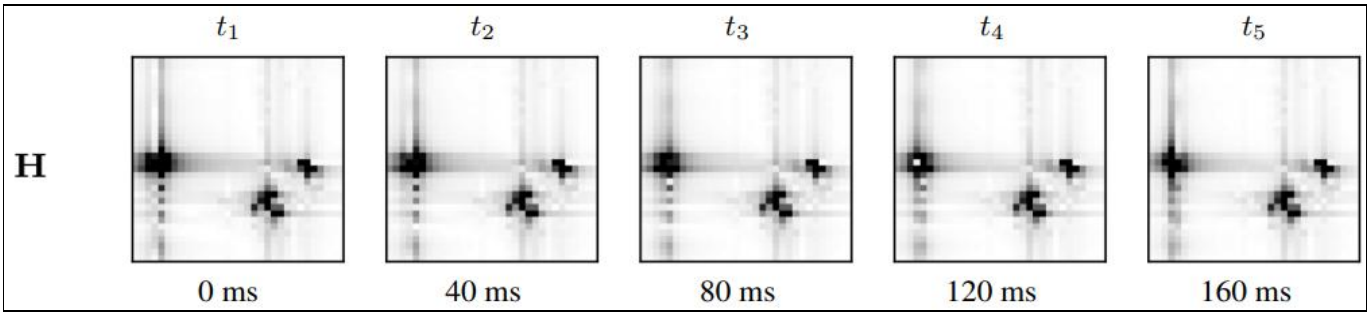
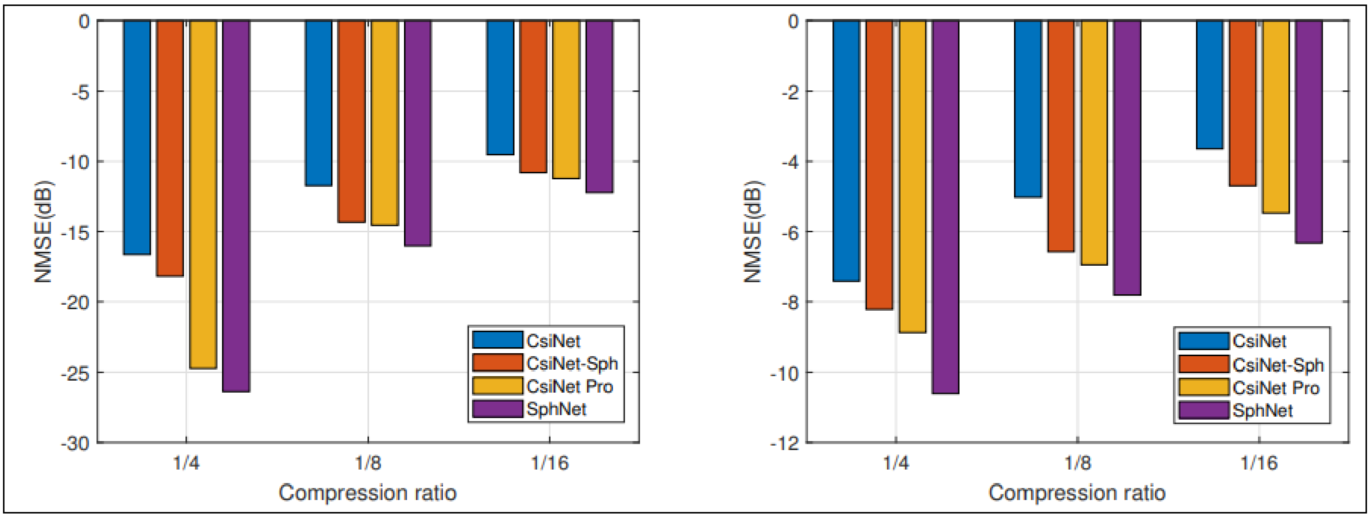


Fig 2: Ground truth CSI (H) for five timeslots (t_1 through t_5) on one sample from the validation set of the outdoor dataset.

4. Results
4.1 Deep Learning for CSI Estimation
Better accuracy may be achieved by optimizing with regard to NMSE and training on spherically normalized data. On the COST2100 dataset, this enhancement is shown in Fig. 3 for CsiNet and CsiNet-Pro. Minmax normalization is used to train CsiNet and CsiNet-Pro, while spherical normalization is used to train CsiNet-Sph and SphNet.



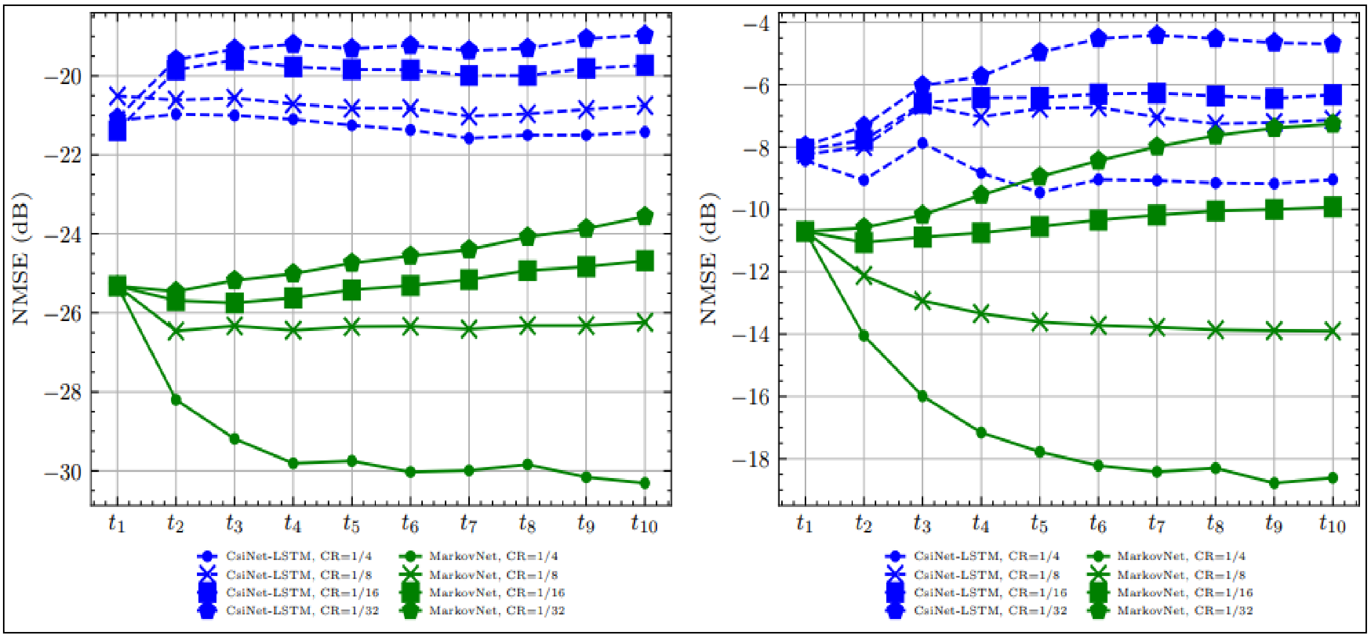
(a) Indoor **(b) Outdoor**

Fig 3: Scalar normalization and its effect on CsiNet and CsiNet-Pro reconstruction errors. The SphNet architecture integrates spherical normalization with CsiNet-Pro.

4.2 Temporal Coherence and Differential Encoding

Using the COST2100 datasets for both indoor and outdoor scenarios, we evaluate Markov Net and CsiNet-LSTM. We train Markov Net for 1000 epochs within the intended timeframe. Next, we initialize the network using the weights from the previous timeslot and train for 200 epochs in each timeslot that follows. We utilize a batch size of 200. The data set is split into a training set consisting of 75,000 samples and a testing set consisting of 25,000 samples so that we may estimate ~.. By reporting the NMSE, we may compare the estimating accuracy of different networks.

4.3 Network Comparison: At four distinct compression ratios, the NMSE of Markov Net and CsiNet-LSTM are shown in Figure 4. Compared to CsiNet-LSTM, all Markov Net instances achieve reduced NMSE in the indoor network. Each Markov Net CR has a lower NMSE than its comparable CsiNet-LSTM CR in the outdoor situation. If the CR is high enough, Markov Net-the channel scenario-shows progressive improvement for future timeslots, but CsiNet-LSTM only demonstrates gradual improvement under outdoor conditions with CR= 14. Figure 5 displays the estimates that were generated from a random sampling of the test set, H.



(a) Indoor **(b) Outdoor**

Fig 4: At different compression ratios (CR), MarkovNet and CsiNet-LSTM were compared using NMSE.

with a CR of fourteen, using CsiNet-LSTM and Markov Nett. Three "peak" magni-tude areas are present in this sample. Although both networks are successful in capturing the two bigger samples, Markov Net successfully retrieves the tiny region of maximal magnitude (green arrow), however CsiNet-LSTM fails miserably (red arrow).

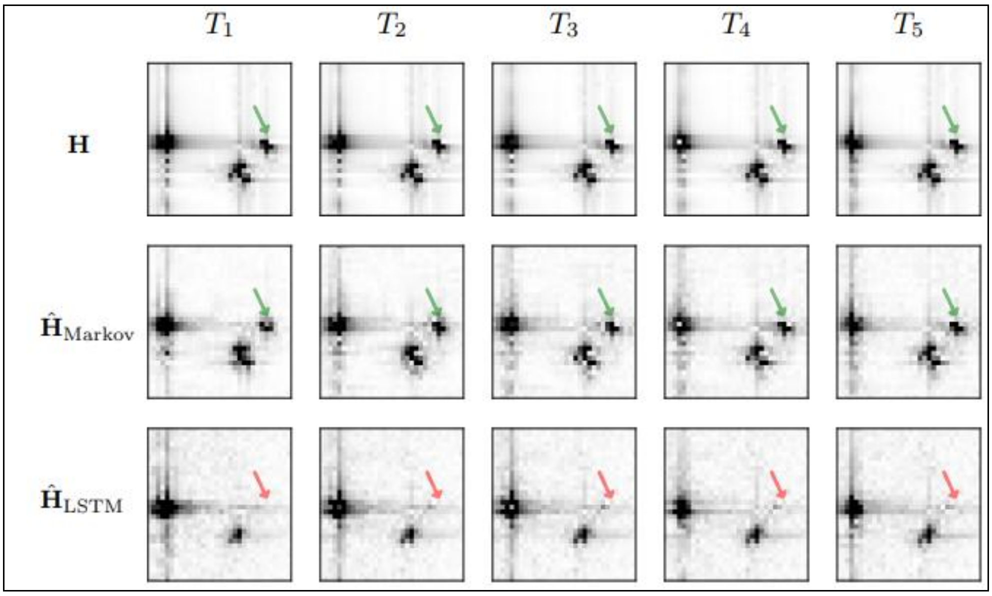


Fig 5: CSI (H), MarkovNet estimates (H_{Markov}), and CsiNet-LSTM estimates (H_{LSTM}) across five timeslots (T_1 through T_5) on one outdoor channel sample from the test set, using CR = ^{1}4.

4.4 Performance under Quantization

We decide to quantify the latent feedback components using -law commanding and uniform quantization so that we may understand how quantization affects the network's performance. To begin, we adjust the feedback scale components, x, logarithmically,

$$f(x) = \frac{\text{sign}(x) \ln(1 + \mu|x|)}{\ln(1 + \mu)}, \ 0 \le |x| \le 1.$$

Uniform quantization is used to provide the desired result after applying equation (3.6) to the signal.

$$\hat{x} = \Delta \left\lfloor \frac{f(x)}{\Delta} \right\rceil$$

where = 2 $^{(b\ 1)}$ to quantify bits by bits. Last but not least, the quantized signal undergoes an inverse logarithmic scale,

$$F(\hat{x}) = \frac{\text{sign}(\hat{x})(1 + \mu)^{|\hat{x}|} - 1}{\mu}, \ -1 \le \hat{x} \le 1.$$

Applying (3.6), (3.7), and finally (3.8) to every feedback element is the abbreviated version of the -law quantization approach that was explained. Both Markov Net and CsiNet-LSTM function under -law quantization where = 255, as seen in Figures 6 and 7, respectively.

When testing in an outdoor setting, there is little variation in network performance over a range of quantization bit densities. On the other hand, when using lower quantization bits There is a significant decline in performance across the board for all network/compression ratios in the indoor situation. One possible explanation is that the Indoor network's far better non-quantized performance (i.e., -20dB to -17dB) compared to the Outdoor network's performance (i.e., -12dB to -5dB) makes a little change in accuracy more noticeable for the Indoor network than for the Outdoor network. Since both networks are taught with continuous feedback, we see that quantization during training might improve their performance.

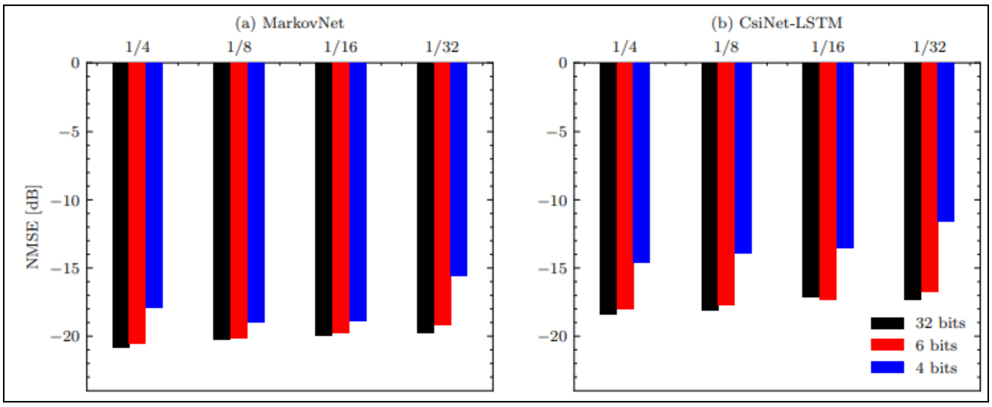


Fig 6: Indoor situation with feed-back due to -law quantization utilizing fixed step size: NMSE comparison of MarkovNet and CsiNet-LSTM, = 2 $^{(b\ 1)}$, for b bits.

4.5 Computational Complexity

The computational complexity is significantly reduced since the resultant network does not need recurrent layers. As can be seen from Table 1, CsiNet, Markov Net, and CsiNet-LSTM all have different amounts of parameters and FLOPs per timeslot. A Markov Net's parameter count.

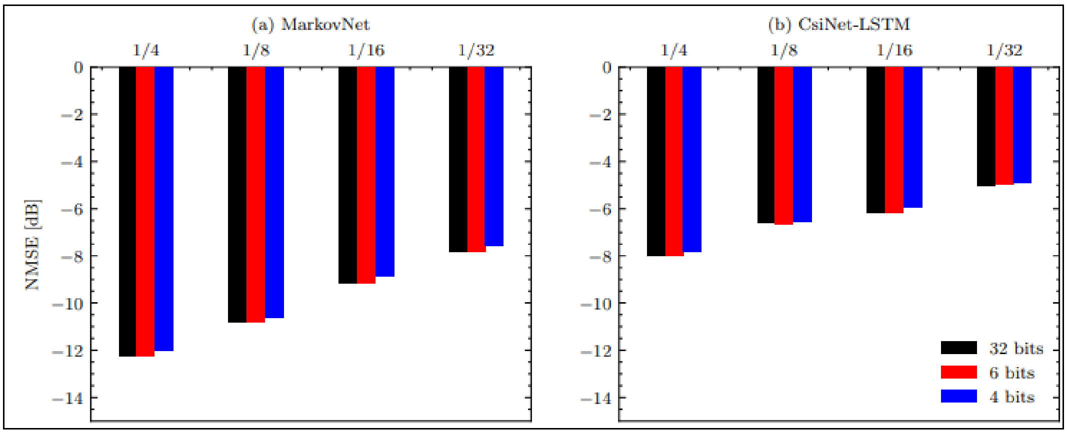


Fig 7: Outdoor situation with feed-back due to -law quantization utilizing fixed step: NMSE comparison of MarkovNet and CsiNet-LSTM size, = 2 $^{(b\ 1)}$, for b bits.

Equals CsiNet, but CsiNet-LSTM necessitates several times as many parameters. Although Markov Net's FLOPs are over ten times lower than CsiNet-LSTM's, the larger kernel size of CsiNet-Pro causes Markov Net to need five to ten times more FLOPs than CsiNet.

Table 1: Computed model size and computational complexity of CsiNet, MarkovNet, and CsiNet-LSTM, two temporal networks that were investigated. A million.

	'arameters			'LOPs		
	ˌsiNet-LSTM	ɅarkovNet	ˌsiNet	ˌsiNet-LSTM	ɅarkovNet	ˌsiNet
ˌR=1=4	32.7 M	.1 M	.1 M	12.9 M	4.5 M	.8 M
ˌR=1=8	23.2 M	.1 M	.1 M	10.8 M	2.4M	.7 M
ˌR=1=16	18.5 M	.5 M	.5 M	09.8 M	1.3 M	.7 M
ˌR=1=32	16.1 M	.3 M	.3 M	09.2 M	0.8 M	.1 M
ˌR=1=64	15.0 M	.1 M	.1 M	09.0 M	0.5 M	.9 M

5. Conclusion

In order to make deep neural networks more effective for estimating MIMO CSI, this dissertation looks at ways to boost their performance. We demonstrated the effectiveness of our suggested spherical normalization method and spoke about the significance of data pre-processing approaches. Chapter showed that a deep differential encoder outperformed recurrent neural networks as a result of optimizing the use of the wireless channel's temporal correlation. Two key innovations were introduced: a heterogeneous differential encoding network that combines autoencoders with deep compressive sensing networks and a precise model for the CSI in the latency domain using sparse frequency domain pilots. Even when faced with aggressive sparsity and noisy pilot estimates, our pilot-based delay domain estimator proved to be accurate. The superior performance of heterogeneous networks compared to homogeneous networks was also confirmed. Our suggested strategy reuses a basic the model on neighboring blocks of many subcarriers; we proved that this route may reduce the network's computational complexity by a factor of 10 while maintaining accuracy.

6. References

1. Chun CJ, Kang JM, Kim IM. Deep learning based channel estimation for massive MIMO systems. IEEE Wireless Communications Letters. 2019;8:1–4. doi:10.1109/LWC.2019.2912378.
2. Khunteta S, Chavva AKR, Agrawal A. AI-based indoor localization using mmWave MIMO channel at 60 GHz. ITU Journal on Future and Evolving Technologies. 2022;3:243–251. doi:10.52953/AORF8087.
3. Lu S. Deep neural network-based channel estimation scheme in massive MIMO systems. Highlights in Science, Engineering and Technology. 2024;119:272–279. doi:10.54097/keag5a17.
4. Li B, Zheng Q, Tian X, Yang M, Gui G, Jiang W, Lei H, Jiang J, Shu F, Elhanashi A, Saponara S. A survey of artificial intelligence enabled channel estimation methods: Recent advance, performance, and outlook. Artificial Intelligence Review. 2025;58. doi:10.1007/s10462-025-11202-0.
5. Khan I, Cheffena M, Hasan MM. Data aided channel estimation for MIMO-OFDM wireless systems using reliable carriers. IEEE Access. 2023;11:2169–3536. doi:10.1109/ACCESS.2023.3269659.
6. Adenekan T. AI-powered machine learning models for IRS optimization in IoT-driven MIMO communication. 2024.