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Original Article

Analyze the Performance of Massive MIMO System Utilizing One Bit ADCs: Deep Learning-Based Approach with Varying SNR and Limited Pilot Resources

Raksha Thakur[1], Vineeta Saxena Nigam[2]

[1,2]*Department of Electronics and Communication Engineering, University Institute of Technology, RGPV, Madhya Pradesh, India.*

[1]*Corresponding Author : rakshauitrgpv@gmail.com*

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Abstract - *One of the essential technologies announced for 5G wireless networks is "Massive Multiple-Input Multiple-Output (MIMO)". This technology incorporates many antennas at the base station, enabling more information signals to be transmitted and received simultaneously on a common radio channel. Massive-MIMO technology empowers deployments such as signal detection, beamforming, channel estimation, etc. Using conventional methods, the requirement of very long pilot sequences is a prevalent issue in obtaining accurate channel estimation. The main objective of this work is to investigate Deep Learning (DL)-centered hybrid Convolution Neural Network with Multi-Layer Perceptron (CNN-MLP) based channel estimation facilitated with one-bit "Analog-to-Digital Converters" (ADCs) in an uplink Massive MIMO scenario. Initially, preprocessing and data preparation are done to evaluate the model. This involves gathering, normalizing, and dividing considered data into training, validation, and test sets. Then, a CNN-MLP architecture will be designed using a deep learning framework with an input layer, several hidden layers, and an output layer for NMSE prediction. By proper training of the proposed model, efficient channel parameters are calculated with fewer pilot lengths to reduce overhead and increase spectral efficiency. By implementing the proposed model, channel estimation accuracy is enhanced efficiently. Simulation achieves better results according to performance metrics such as NMSE and attainable SNR per antenna. Results showed that "NMSE" performance approach as low as -22.2dB as the number of antennas increases while "SNR per antenna" achieves 99.5% gain for varying received SNRs of 0dB, 10dB, and 20 dB even at smaller pilot length.*

Keywords - *Massive MIMO, One-bit ADCs, Channel estimation, Deep Learning (DL), CNN-MLP.*

1. Introduction

Massive MIMO in 5G technology utilizes many antennas in base stations to enhance spectral efficacy, durability, and energy efficacy compared to smaller-size MIMO. However, increasing the number of base station antennas also leads to higher power utilization, greater hardware intricacy, and improved system expenditure [1].

Within the realm of 5G communication systems, integrating Multiple-Input, Multiple-Output (MIMO) technology poses a notable obstacle: the considerable power consumption linked to numerous Radio Frequency (RF) chains. Nonetheless, even by accepting a modest performance compromise, authors in [2] have investigated a possible remedy by adopting low-precision ADCs. This research has scrutinized pivotal aspects concerning millimeter-wave (mmWave) massive MIMO systems reliant on these low-precision ADCs. These issues encompass various dimensions: transmit precoding, channel information feedback, channel estimation, and signal identification. Likewise, other approaches like mixed-ADC architectures have arisen for overall system efficacy.

The practical deployment of 5G in a massive MIMO connectivity featuring ADC quantizers remains a persistent task, yet it holds the potential for fostering more efficient and sustainable communication infrastructures. Conversely, hardware costs and power usage get mitigated by opting for few-resolution ADCs (i.e., 1 to 3 bits). However, authors in [2] also indicate modest performance loss while using 3-bit in 'm-bit' ADCs whenever the spectral efficacy closely approximates the perfect scenario of infinite resolution (m =

∞). Additionally, leveraging many antennas can mitigate the loss in spectral efficacy caused by low-resolution ADCs. Since the number of comparators in a m-bit ADC increases linearly with m, the complexity and energy consumption of an ADC increase linearly with resolution. As a result, compared to higher-resolution ADCs, lower-resolution ADCs are substantially less costly and use less power.

According to information theory, using a large-scale antenna array with low-resolution ADCs at small SNR values guarantees adequate system performance. A convincing trade-off between spectral and energy efficacy can be accomplished using ADC quantizers at small SNR values. For instance, compared to the full-resolution signal, a two-bit ADC receiver experiences only a 5% spectrum loss at 0dB, while a three-bit ADC receiver encounters just a 15% spectrum loss at 20 dB.

This discovery highlights the great enhancement in the progress of receiver technology in wireless communication employing low-resolution quantization integrated with lower-bit ADCs [3, 4]. According to [5], low-precision ADC is utilized when constructing high-bandwidth communication networks. In systems with abundant bandwidth, the slight decrease in spectral efficacy using a low-precision ADC is tolerable when working at low to moderate SNR.

On the other hand, Massive MIMO systems also encounter challenges related to extensive data processing, elevated hardware expenses, and substantial overall power usage. Authors in [6] addressed these issues effectively using a practical solution with finite-resolution ADCs. Numerous research findings indicate that employing low-resolution quantization technology yields notable performance enhancements while maintaining an acceptable level of capacity loss.

In modernistic systems, base station data converters typically employ ten-bit highly precise converters during transmission. However, in massive MIMO scenarios with 100's and thousands of antennas, the same issue of related costs and power utilization become exorbitant. Additionally, there may be bandwidth overload due to the front-haul link. To overcome this, a practical approach is to reduce this resolution. Instead of using 10-bit converters, systems could employ 1 or 2-bit converters. Also, the power usage of ADCs remains the primary contributor to the overall utilization of power required for the RF chain.

Primarily, the power consumption for ADCs increases linearly in tandem with the sampling rate, a consequence of the extensive BW of mmWave signals. Furthermore, power usage escalates exponentially with the ADC resolution of 'm' using the standard flash manner 'm-bit' ADC. Presently, economic high-speed ADCs (≥ twenty GigaSample/sec) with high resolutions (typically approx. 8 to 12 bits) exhibit a power utilization of approximately 500 mW. By featuring 512 ADCs and 256 RF chains in the context of a Massive MIMO system, the collective power absorption of circuits could soar to 256 W, potentially surpassing the practical feasibility of the system [2].

Consequently, the base station would be highly affected by the utilization of the present high-resolution ADCs (8–12 bits) and fast-speed for each antenna array [7, 8, 9]. As a result, using inexpensive, low-resolution ADCs (1-4 bits) is encouraged as a possible alternative for this issue.

Another study in [10] used low-resolution quantizers, which introduced significant nonlinear distortion into the output signal compared to conventional high-resolution quantizers. Consequently, various research methodologies and quantization error models are essential for investigating low-resolution ADCs.

Previous studies have predominantly centered around high-resolution quantization. However, [11] used a novel method that separates the quantization procedure from the back-end baseband processing, making it possible to use a model of the quantized output signal to analyze how quantization resolution affects system performance.

Above all, literature concerning low-bit ADC receivers is mentioned. It was found that problems such as data processing, elevated hardware expenses, and substantial overall power usage were encountered while using high-resolution ADCs. Using low-bit ADCs, issues like slight performance loss in terms of spectral efficiency can be mitigated by having more antennas. This proposed work mainly focuses on channel estimation using low-bit ADCs for a Massive MIMO network.

Therefore, the present study aims to analyze the performance of Massive MIMO systems utilizing One Bit ADCs and DL algorithms. The main objective of the present study is:

i) To boost the efficiency of the Massive MIMO network, the known observations of channel parameters and deep learning network are exploited to attain mapping between received quantized matrices and channels. For this, a CNN-MLP neural network is employed.
ii) An explicit channel prediction can be accomplished by employing a CNN-MLP deep learning model, a greater number of antennas, and smaller pilot lengths.
iii) To evaluate the performance of the proposed model, the simulation is performed using the DeepMIMO channel dataset based on an openly available ray-tracing setup. Results show that the proposed model performs better than existing approaches by considering performance metrics such as Normalized Mean Squared Error (NMSE) and attainable Signal-to-Noise Ratio (SNR) with varying antenna sizes and pilot lengths.

1.1. Paper Organization

The paper's organization is stated as follows: Section 1 briefly introduces Massive MIMO Network, One bit ADC's. Section 2 shows the related literature review based on various deep learning techniques for channel estimation in the Massive MIMO network. System and channel model proposed hybrid model architecture, followed by the Proposed Scenario and dataset preparation in Section 3, and Simulation Results and Discussion in Section 4. Finally, the paper is concluded in Section 5, followed by a future scope.

2. Literature Review

Traditional signal processing techniques have created effective channel estimate methods and low-complexity near-Maximum Likelihood (ML) data detectors for massive MIMO systems. The requirement for extended pilot sequences to attain reliable Channel Estimation or data detection performance is a common problem these technologies encounter. Machine learning techniques have been assessed to solve problems related to 1-bit "Analog to Digital Converter" (ADCs). Some proposed deep-learning approaches are discussed below:

Deployment of Channel Estimation (CE) in massive MIMO using low-bit ADCs plays a crucial role in designing effective precoders. To achieve optimal precoder design, accurate channel estimation is essential. The work in [12] estimates the Base Station (BS) channel vectors using low-bit ADCs. The estimation process relies on pilot-dependent channel training by assuming perfect synchronization between the Base Station and user terminal, employed under a Time-Division Duplex (TDD) protocol.

During the uplink phase, channel estimation training occurs, and the same pilot is used by User equipment across all cells. Some research has already been discussed for low-resolution ADCs using conventional and machine-learning approaches. The major issues examined in existing machine learning models, such as OFDM systems, perform channel estimation but solely for systems using a single antenna [13]. In [14], the method only functions in lower dimensions MIMO regimes because it cannot focus on a high number of antennas. In [15], channels are estimated only using received signals from fully-resolution converters.

In [16], the authors explore deep learning dependent channel estimate framework for Uplink massive-MIMO systems featuring 1-bit ADCs. This approach hinges on past channel estimation data and derives channel information by associating it with the received quantized measurements using deep neural networks. Researchers address the challenge of channel estimation with enormous 1-bit Analog-to-Digital Converters (ADCs) and antenna arrays in wireless networks. A novel approach has been proposed in [17] that leverages a deep generative pre-trained model. Optimizing the input vector of the defined model aims to maximize a correlation-based loss function.

Recent research uses Generative Adversarial Networks (cGAN) for finding channel parameters using one-bit quantization [18]. Another work was done using an LSTM-Gated Recurrent Unit (GRU), and the authors designed an integrated model for channel estimation [19]. In [20], BiLSTM is proposed to utilize improved training ability, moving toward precise CE in their proposed system model. These systems deliver high-level performance but require complex models and significant processing resources.

3. System Model

3.1. System and Channel Model

During the uplink transmission, trained pilots (p) are transmitted by the user's transmitter (Tx) to the base Station receiver (Rx). The Base Station obtains Channel State Information using channel estimators and then uses the signal it receives to conduct symbol detection. These trained pilots help to handle pilot contamination, minimize overhead, exploit channel reciprocity, and enable scalable channel estimation in massive MIMO systems.

In this scenario, a user is equipped with a single-antenna communicating with a base station with 'Nr' antennas in a massive MIMO system, employing one-bit quantization in the receiving chain, as depicted in Figure 1. Time Division Duplexing (TDD) is utilized for Massive MIMO, leveraging channel reciprocity to eliminate the necessity for bidirectional channel estimation and CSI feedback. Consequently, downlink precoding can be executed in TDD mode utilizing the uplink CSI estimate derived from pilots transmitted by the User Equipment (UE).

During the uplink stage while doing training, the UEs transmit pilots with length $\mathbb{N}$ to the BS, and through one-bit ADCs, quantized signal vector $Y \in C^{Nr \times \mathbb{N}}$ will be received, which is defined as

$$Y = \operatorname{sgn}\left(hp + n\right) \tag{1}$$

Where n denotes the noise matrix elements following $CN(0, \sigma^2)$, $h \in C^{Nr\times 1}$ is the channel matrix, $p \in C^{\mathbb{N}\times 1}$ is a pilot matrix, and $\operatorname{sgn}(\cdot)$ represents the signum function, which is individually applied to the real parts (Re) and imaginary (Im).With $j = \sqrt{-1}$, the quantization output belongs to $\{-1+j, -1-j, 1-j, 1+j\}$. Using the training signal '*p*' and observations 'Y', the goal is to estimate channel 'h'.

Using a ray-tracing model, the channel is designed with K paths. Each path 'l' has $\boldsymbol{\theta}_l$, ϕ_{rl}, and ϕ_{tl} as the strengths, angles of arrival, and angle of departure individually. Hence, the channel matrix is,

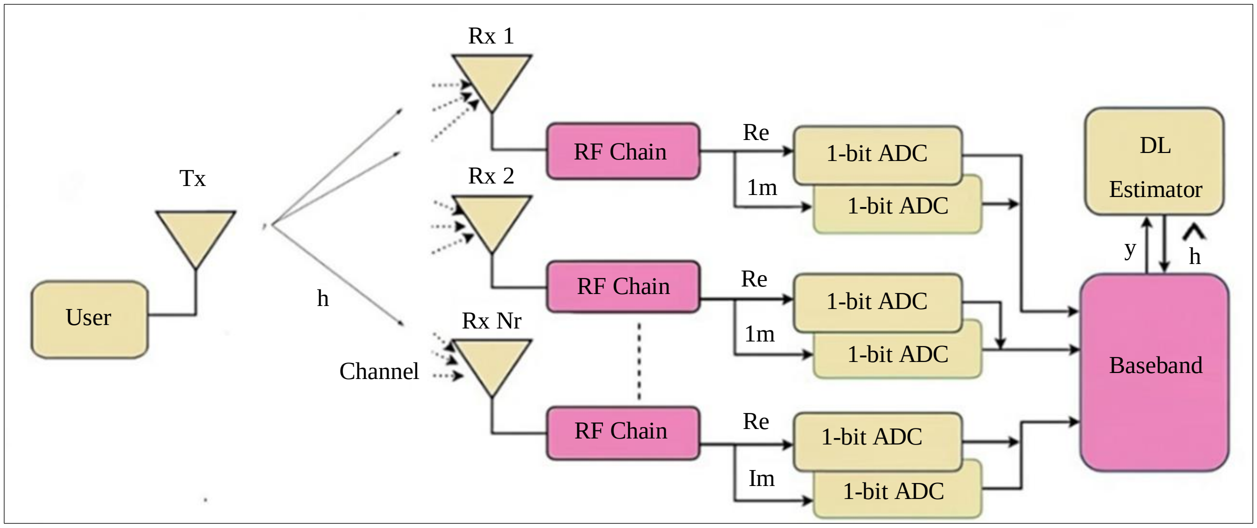


Fig. 1 The block structure of the massive MIMO system aided by Deep-Learning estimator

$$h = \sum_{l=1}^{K} \theta_l a(\phi_{rl})\, a(\phi_{tl}) \tag{2}$$

Where a (ϕ_{rl}) and a (ϕ_{tl}) are array response vectors of BS and user equipment.

The estimated Channel vector $\hat{h}$ is constructed using the received quantized signal (Y), as shown in Figure 1. During downlink information transmission, a beamforming vector can also be obtained using an estimated channel vector ($\widehat{h}$), hence the received SNR per Tx. antenna can be written as:

$$SNR = \frac{\rho r}{Nr} \frac{|\widehat{h}^H h|}{\|\widehat{h}\|^2} \tag{3}$$

Where, ρr is the average received SNR before beamforming.

3.2. DNN Approach for Channel Estimation

With lower-bit resolution ADCs in MIMO setup, estimation of channel parameters becomes a significant hurdle due to the nonlinearity introduced by receivers in the received signals. A recent study [21] has proposed a novel deep-learning architecture to mitigate this challenge by addressing signal detection, pilot sequencing, and channel estimation.

Specifically designed networks for channel estimation and signal detection, presented by the uniqueness of quantization properties in low-bit systems, establish promising outcomes in simulations, showcasing considerable improvements in precise parameter estimation via deep learning modeling.

Utilizing the deep learning model, it is easy to perform the mapping among the channel and received quantized matrices, which potentially reduces the pilot length requirement. This mapping type will be of great importance when large antenna arrays are installed. The mapping function exists if the pilot arrangement is built to meet the length constraint and the angles of the intricate pilot symbols consistently sample within the array.

3.2.1. Mapping Back Received Quantized Signal to Channels

When BSs are deployed in a certain environment (Indoor or Outdoor), they will often encounter the same channels repeatedly. Therefore, the fundamental relationship between the channels and quantized received signals might be discovered by utilizing prior experience.

This could lead to a large reduction in the pilot's length. In light of this, the proposed article suggests discovering the mapping of the channel to the quantized received signal using a deep learning model. Assuming received quantized matrices {Y} and channel set {h} then the mapping function is defined by $\psi(\cdot)$:

$$\psi : \{Y\} \rightarrow \{h\} \tag{4}$$

Postulate 1: Considering the above-proposed System and channel model by putting the value of n = 0 in Equation (1) and the sequence of channel {h}. Therefore, the angle of θ in the Equation is defined as:

$$\theta = \min_{\substack{\forall h_m h_n \in \{h\} \\ m \neq n}} \max_{\forall Nr} \left| \angle [h_m]_{Nr} \angle [h_n]_{Nr} \right| \tag{5}$$

Mapping function $\psi(\cdot)$ exists if the pilot signal having length $\mathbb{N}$ is constructed, which fulfilling $\mathbb{N} \geq [\pi/(2\theta)]$ where complex symbols of pilot lie in the range $[0,\pi/2]$ in an equal manner. The verification of Postulate 1 and Equation (5) is explained in the study of [16].

Postulate 1 stated that if the pilot arrangement is built using the predetermined model given in the proposal, a unique mapping $\psi\ (\cdot)$ exists that will map the quantized received matrices Y to the channel h. It is important to note that, as demonstrated in the simulation results also with the stable learning abilities of the proposed learning method will have a high chance of attaining this mapping $\psi\ (\cdot)$, which will further supportive to minimize the overhead associated with channel training as compared to conventional CE methods. Driven by this incentive, the proposed CNN-MLP-based learning model shows the capability to attain this mapping.

3.2.2. Reduction in Pilot Requirement Attributed to Antenna Growth

According to Postulate 1 and its proof, a unique channel in set {h} can guarantee a unique received quantized matrix by the chosen pilot length sequence. Eventually, many BS antennas result in unique received quantized matrices with the same UL pilot length. These antennas will provide a finer channel estimation, as shown in simulation results. Hence, bijectiveness in mapping from {h} to {Y} is maintained with increased BS antenna along with reduced pilot signal requirement [16].

Corollary 1: Assuming the Line-of-sight channel model has a single path for BS and half wavelength antenna separation for the uniform linear array. The minimum difference between any two angles of arrival for any 2 users $\phi 1, \phi 2 \in [0, \pi]$ is given by $\tau\phi$. If the pilot sequence is built to meet the necessity of postulate 1, then the mapping will exist, and pilot length is defined by:

$$\mathbb{N} = \left\lceil \frac{1}{(\mathrm{Nr}-1)\left(4\sin^2\left(\frac{\tau\phi}{2}\right)\right)} \right\rceil \tag{6}$$

The above Equation is proved in [16] and implies in postulate 1. The exciting feature of the proposed CNN-MLP model, which requires additional antennas and fewer pilots to ensure the availability of $\psi\ (\cdot)$ and the same channel estimate quality, is stated in Corollary 1. In some way, numerical simulations in sub-section 4.1 also validate this exciting observation.

3.3. Proposed Hybrid Model Architecture

For channel estimate in wireless communications, a combined CNN-MLP architecture based on limited pilot length when a large number of antennas is utilized, as shown in Figure 2. In this scenario, a hybrid CNN-MLP model for channel estimation can leverage the resilience of both CNNs and MLPs to extract spatial features and then process them for accurate channel estimation. Convolution procedures are applied to extract local features from the input data. The convolutional layers will capture the data's spatial features, often applied with activation function-rectified linear units or ReLUs. Then, it is applied to two stacks of fully connected layers, which can learn complex feature combinations to generate channel predictions. ReLU follows this by adding non-linearity between layers and dropout layers to stop overfitting while training. The ending stack involves a fully connected output layer with just '2Nr' neurons.

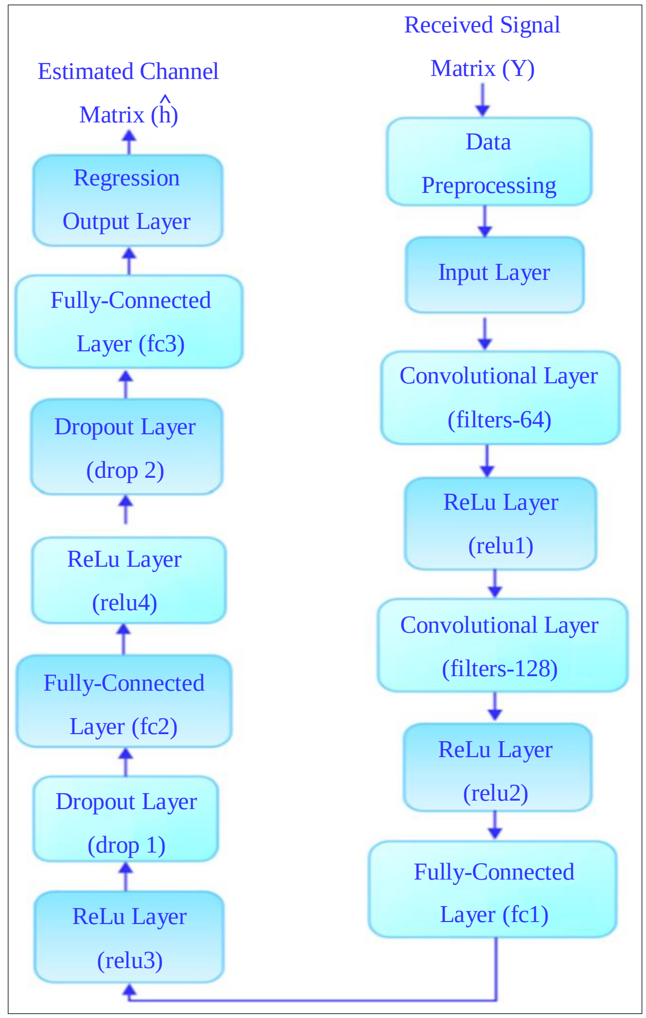


Fig. 2 Architecture of proposed neural network

Here, a regression learning issue is overcome by minimizing the loss function for better prediction of channels during the network training to obtain the required results. For that purpose, ADAM as the optimizer and Normalized Mean Squared Error (NMSE) are considered for network training. Normalized mean square error or the difference between the real channel matrix (h) and the estimated channel matrix ($\hat{h}$) can be minimized by adopting a better channel estimation scheme. Figure 3 shows that before commencing the training, the network requires data pre-processing of its inputs and outputs to ensure efficiency in model training. Initially, by considering the determined accurate channel value obtained from the training model, datasets get normalized to the range of [-1, 1] whether the dataset is in the training or testing phase for all channels. As prior research [22, 23] demonstrated, this normalization step has proven highly beneficial. Next, vectorizing the obtained quantized measured matrices. Lastly, as real-valued computation is widely used in deep learning frameworks, both channel and quantized received matrices are separated into real and imaginary factors and then compressed into different vectors.

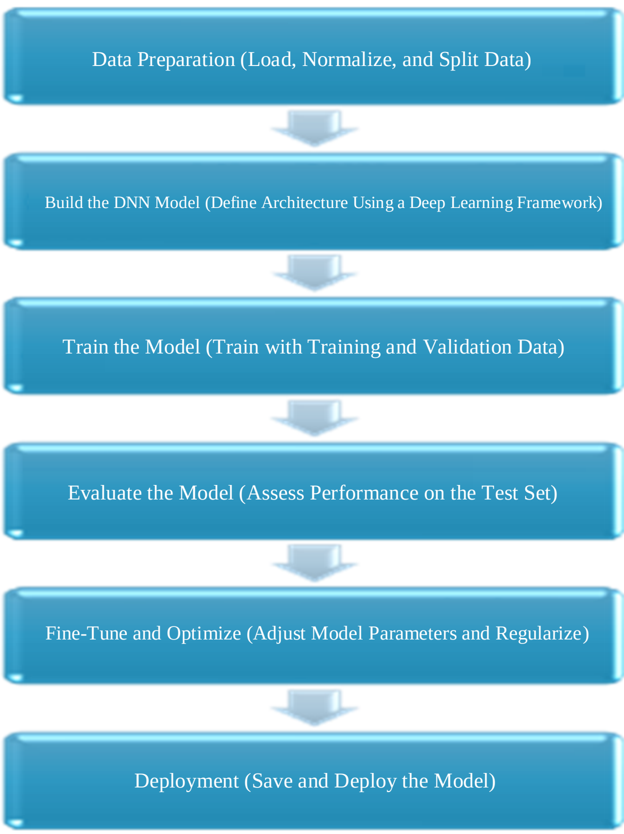


Fig. 3 Flowchart of the proposed algorithm

Table 1. Network parameters

Parameter	Set value
Antenna Sizes	2,10,30,60,100
Pilot Lengths	2,5,10
Optimizer	Adam
Initial Learning Rate	0.0001
Batch Size	32
Total Samples	151402
Train Samples	121121 (80%)
Test Samples	30281 (20%)

Table 2. Dataset preparation

Parameter	Set value
Scenario Name	I1_2p4 (Figure 4)
Active BS's	32
Active Users	Rows 1 to 502
BS Antennas	[1,100,1] (x,y,z)
System BW	0.01 GHz
OFDM Sub-Carriers	1 (only carrier)
Number of Multipaths	10 (Figure 5)
Number of Multipaths	1 (Figure 7)

3.4. Proposed Scenario and Dataset Preparation

In this simulation, the proposed scenario in Figure 4. is sourced from the DeepMIMO dataset developed with the help of Remcom Wireless InSite's Ray tracing simulator [24, 25]. The generated DeepMIMO dataset includes the channels connecting each potential user location to each antenna at the BS. The detailed parameters and assigned values in the dataset are mentioned in Table 2.

This DeepMIMO dataset is then used to train the model by separating it into two: - 80% training and 20% testing. Moreover, due to limited computational resources, the model is trained with a smaller batch size of 32, epochs of 20, and a learning rate of 0.0001 with an Adam optimizer having NMSE as a loss function, as mentioned in Table 1. The variation of the SNR between the true channel matrix (h) and the estimated channel matrix ($\hat{h}$) is computed by employing Normalized Mean Square Error (NMSE).

$$\text{NMSE}= 10\log\left\{\mathbb{E}\left[\frac{\|h-\hat{h}\|^2}{\|h\|^2}\right]\right\} \tag{7}$$

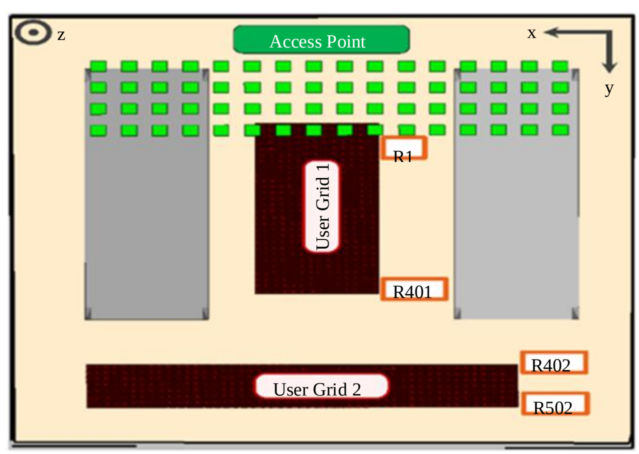


Fig. 4 The top view of the 'I1' scenario [25]

4. Results and Discussion

This section showcases the performance of the Massive MIMO channel estimation and its evaluation with the help of numerical results obtained through the proposed model-driven CNN-MLP Learning network. All simulation work is performed using MATLAB software. The proposed work evaluates the hybrid learning model-based channel estimation, compares them with previously found results, and shows how this model generates improved results. The applied model analyses the performance of NMSE based on the deepMIMO dataset generated at SNR values 0 dB, 10 dB, and 20 dB. Enabling DL with one-bit ADC, where the proposed approach proves that choosing the proper length of pilot generates a unique mapping between ‘Y’ and ‘h’ and shows that by using a smaller pilot, better prediction of channel parameters can be possible.

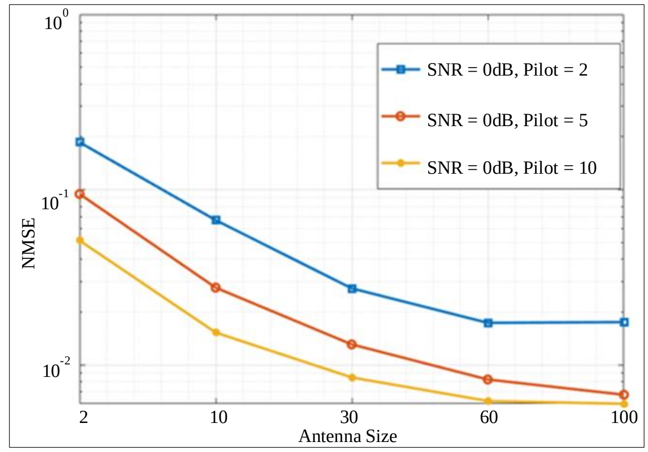
4.1. Simulation Results and Evaluation

This work focuses on a hybrid CNN-MLP-based model for varying pilot lengths, i.e. 2,5 and 10 and various SNR ranges concerning NMSE at different numbers of antennas such as Nr= 2,10,30,60 and 100, as shown in Figure 5. Here, results show that even with smaller pilot lengths, i.e. pilot=2 and pilot=5, NMSE approaches nearly to -18dB to -20dB range as the no. of antennas reaches to 100, as presented in Figure 5(a), which will help to provide accurate channel prediction. When pilot length gets increased to 10 at SNR 10dB, NMSE reaches up to -21.5dB at increased antenna size as in Figure 5(b), whereas with increased SNR=20dB, even at smaller antenna size, achieved NMSE attains -20dB and goes up to -22.2dB as shown in Figure 5(c). Hence, the proposed approach proves the validity of results through simulations by stating that fewer pilot lengths help reduce channel overheads.

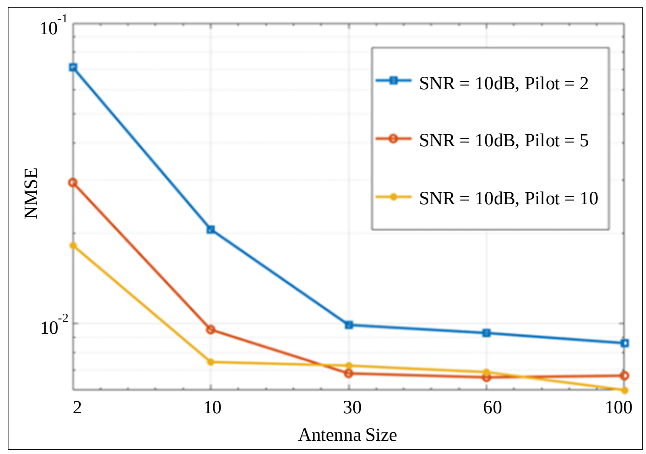
From the existing theories, it is already known that if there are more antennas, the system has additional spatial degrees of freedom, which helps increase diversity gain and spatial multiplexing. This will also help mitigate channel distortion, such as fading and interference, to a greater extent, which further helps lower NMSE. The channel estimation overhead is reduced when using fewer pilots, which helps improve spectral efficiency and resource allocation. However, in “one-bit massive MIMO” systems, quantization introduces nonlinearity and fewer pilot results, compromising channel estimation accuracy.

However, introducing the proposed learning approach along with a greater number of antennas and higher SNR often outweighs the effects caused by nonlinearity and fewer pilot usage, resulting in improved overall performance. Hence, the proposed model results show that explicit channel prediction can be achieved even with a few pilots.

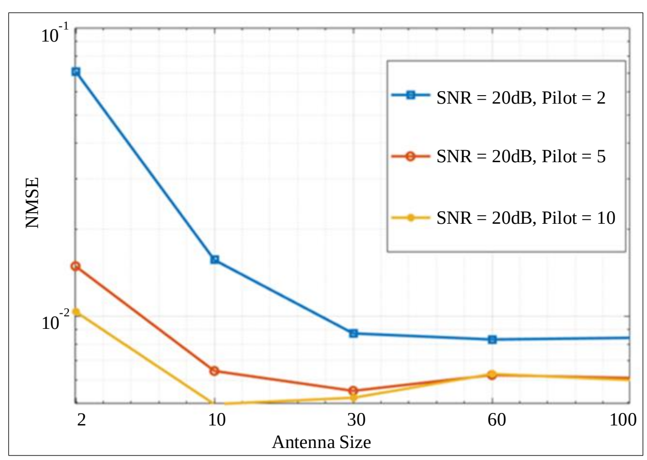
Figure 6 shows the comparison of the combined performance of NMSE for all pilot lengths (2,5,10) at various received SNR ranges (0dB,10dB,20dB) and with varying antenna sizes and results represent that NMSE decreases as pilot size and antenna size increases.



(a)



(b)



(c)

Fig. 5 Performance of NMSE enabled with DL estimation for (a) SNR fixed at 0 dB, (b) SNR fixed at 10 dB, and (c) SNR fixed at 20 dB.

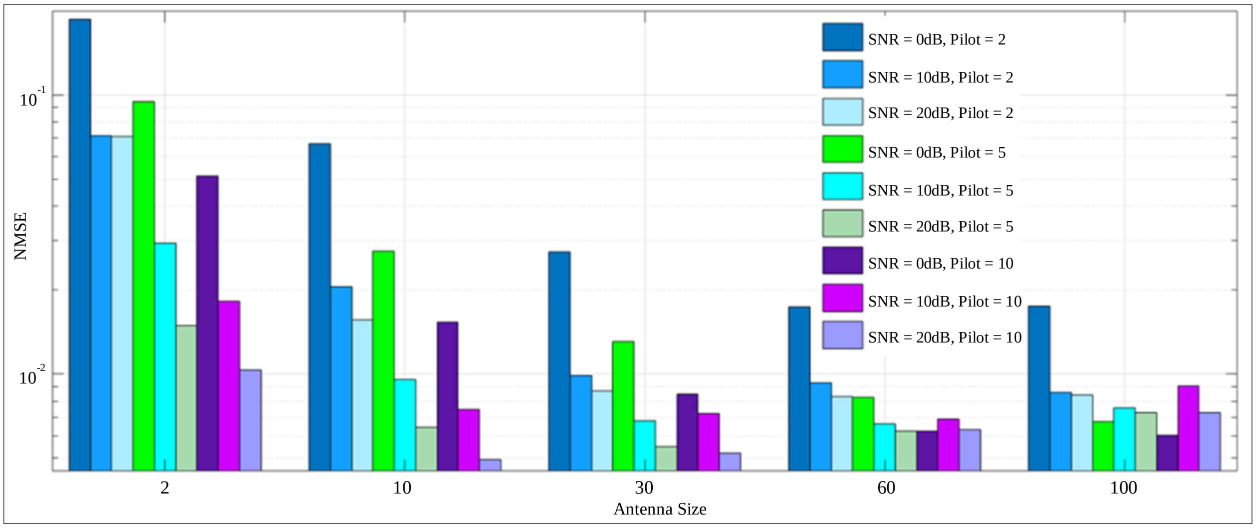
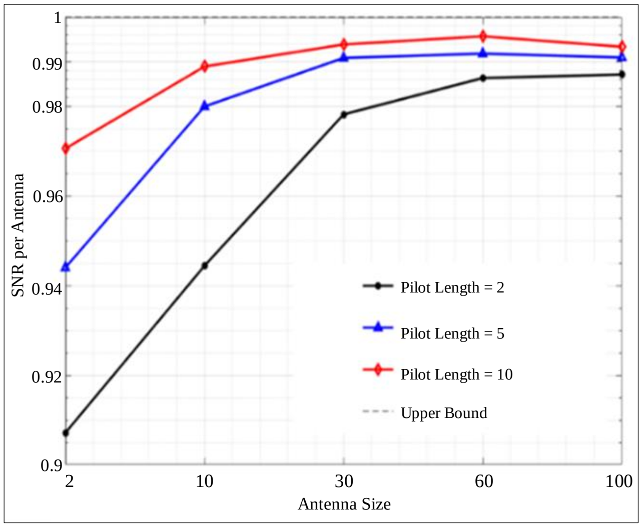


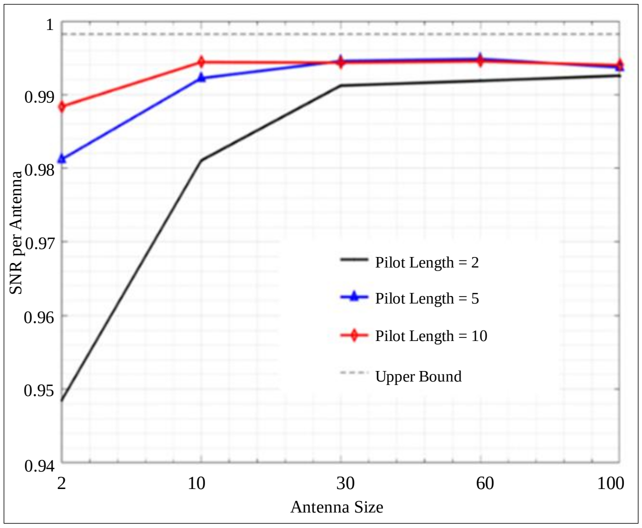
Fig. 6 The combined performance of NMSE for increased Antenna size with varying pilot lengths and SNR's

Increased model complexity typically reduces NMSE in CNN-MLP models for channel estimation in massive MIMO networks. This affects real-time inference capabilities and overall latency, memory use, and computational cost. Optimization strategies while designing models like quantization or creating specialized network designs that preserve accuracy while lowering complexity strike a tradeoff between NMSE and computing efficiency.

Figure 7 represents another comparison of results between 'SNR per antenna vs Antenna sizes' for various pilots, i.e. 2,5, and 10. These comparisons are performed for measured received matrices of SNR values fixed at 0dB,10dB, and 20 dB. In earlier research, it was noticed that there exists a small drop in SNR for pilot length =2 at 0dB at smaller antenna size, but this drop will be reduced further as antenna size and pilot lengths increase. This drop is considered when the expansion of overall SNR does not match the rate at which antenna size increases. In Figure 7(a), with the proposed model, even at a smaller pilot length and antenna size of two, the attainable SNR per antenna can be achieved at approximately 91%. Further, it gets better and goes up to 99.5% as antenna size increases for all presented pilot lengths and received SNR. In Figure 7(b), an attainable SNR w.r.t antenna size of two achieves better performance for all the pilot ranges and further improves with increased antenna size. Similarly, it is analyzed from Figure 7(c) that for pilot lengths 5 and 10, at smaller antenna sizes, the attained SNR is close to the upper bound. From all cases in Figure 7, it is concluded that as the antenna size increases, mapping between the quantized received signal and channel becomes more equipped. Thus, this increased pilot length and antenna size results in the performance of attainable "SNR per antenna" reaching close to the upper bound. It will be further improved by finer tuning the model hyperparameters to optimize predictive accuracy.



(a)



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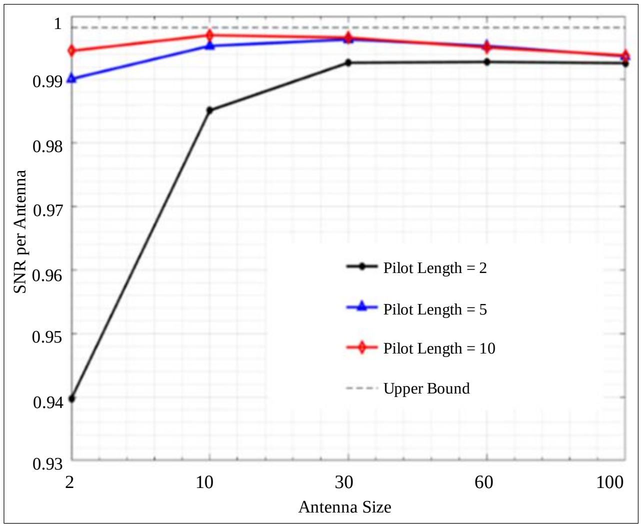

(c)

Fig. 7 Performance of SNR per Antenna concerning the Antenna size with varying pilot sizes using DL estimators (a) SNR fixed on 0 dB, (b) SNR fixed on 10 dB, and (c) SNR fixed on 20 dB.

4.2. Comparison of Proposed Model with Previous Results

Figure 8 shows the comparison of the proposed model with other models such as MLP [16] and non-ML model, i.e. Expectation Maximization Gaussian-Mixture Generalized Approximate Message Passing (EM-GM-GAMP) [16] for pilot length=10. The result represents that non-ML models attain nearly -5dB to 0dB while MLP approaches around -16dB to -20dB while the improved performance of the proposed model achieves better results for both ranges of received SNRs (0dB and 10dB).

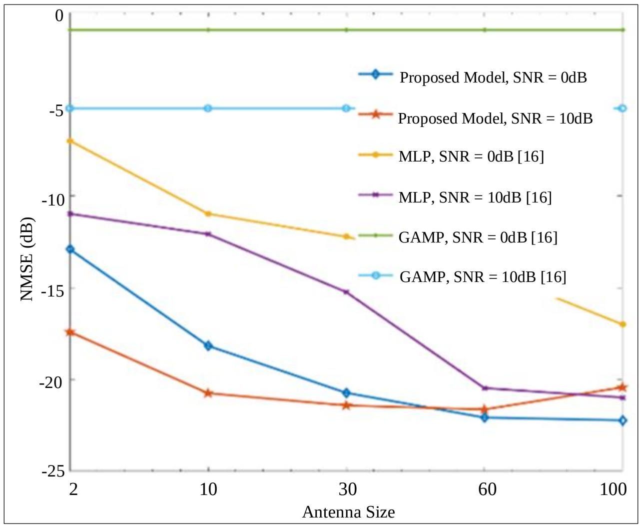

Fig. 8 Comparison of the hybrid proposed model with existing models for Pilot length=10

Similarly, Figure 9 shows the comparative performance of the proposed model for pilot length 2,5,10 with existing studies performed at pilot length =8 using MLP and CNN at SNR 0dB, 10dB, and 20 dB [18]. It is evident from Figure 9 that the NMSE achieves approximately −22 dB with increased SNR values, while other models range between −6 to −13dB NMSE. Hence, the proposed models attain a gain of approximately 9 to 16% compared to existing work [18].

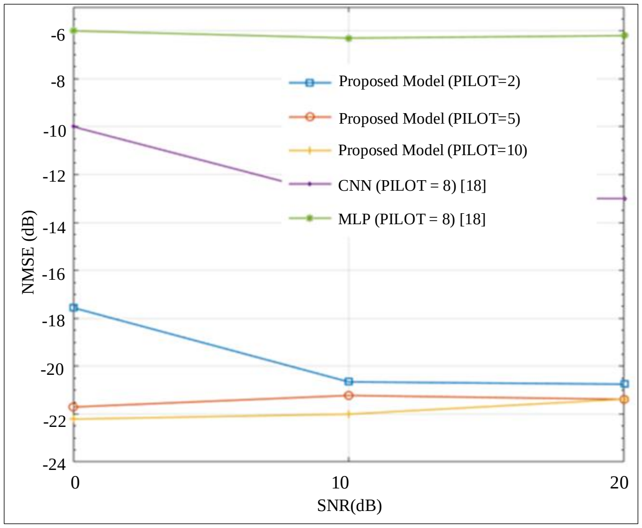

Fig. 9 Comparison of the hybrid proposed model with other models for varying pilot

Table 3 Represents the numerical results of NMSE of the proposed models for pilots 2,5, which is way better than existing CNN and MLP models at larger pilot length=8.

Table 3. Performance comparison

SNR	CNN (P=8)	MLP (P=8)	Proposed (P=2)	Proposed (P=5)
0 dB	-10	-6	-17.6	-21.7
10dB	-13	-6.3	-20.7	-21.2
20dB	-13	-6.3	-20.8	-21.4

4.3. Discussion

This section discusses the comparison between the obtained results with already existing models. This research focuses on Massive-MIMO channel estimation, and its evaluation is performed using a hybrid CNN-MLP Learning model. Based on the postulates mentioned in subsection 3.2.1, the fundamental association between the channels and quantized received signals is established by utilizing prior knowledge of channel behavior. This will lead to a large reduction in the pilot's length. With stable learning abilities, the proposed learning model will have a high chance of attaining this mapping ψ (·), further supporting minimizing the overhead associated with channel training. The exciting feature of this suggested CNN-MLP model is that having fewer pilots requires large antennas at BS to ensure the unique mapping of ψ(·) and accurate channel estimate, as mentioned in subsection 3.2.2. The proposed work evaluates estimation accuracy using metrics such as NMSE and attainable SNR per antenna for reduced pilot lengths and varying antenna sizes, compares the obtained results with previous findings, and shows how this model performed better than the existing one. Simulation Network hyperparameters and dataset preparation are mentioned in Tables 1 and 2. Simulated results of reduction in NMSE vs Antenna size for varying pilots are represented in Figure 5(a) SNR=0dB, (b) SNR= 10dB, and (c) SNR=20 dB. Figure 6 shows the combined comparison of NMSE concerning different SNR ranges.

Figure 7 compares results between ‘SNR per antenna vs Antenna sizes’ for various pilots, i.e. 2,5, and 10, at measured received matrices of SNR values fixed at 0dB,10dB, and 20 dB. The proposed model has improved NMSE and Attainable SNR per antenna at -22.2dB and 99.5%, respectively. Figure 8 shows the comparison of the proposed model with existing MLP [16] and non-ML model, i.e. expectation maximization Gaussian-mixture generalized approximate message passing (EM-GM-GAMP) [16] at pilot length=10 and results in improved NMSE performance.

Figure 9 shows the comparative analysis and shows that the proposed model attains improved results compared to CNN and MLP models alone, even in the presence of more pilots across all SNR values. For instance, the proposed model with a smaller pilot=2 results in reduced NMSE than pilot=8 in other models like CNN and MLP [18].

5. Conclusion

This work focuses on improving channel estimation performance for a one-bit massive MIMO system using the proposed hybrid CNN-MLP model with fewer pilots and large BS antennas. The proposed model helps address the challenges of estimating the massive MIMO channel when the base station utilizes one-bit Analog-to-Digital Converters (ADCs). Numerical results indicate that the proposed technique significantly boosts channel estimation efficacy while maintaining a reasonable NMSE performance of -22.2dB, even with reduced pilot length. Further simulation performance shows that with increasing antenna sizes and varying pilot lengths, the attainable SNR rate approaches 99.5% and is further improved to reach the upper bound.

Further work will be done to enhance the NMSE performance by considering other complex Deep Learning models. Future research can also be extended to additional channel models used beyond 5G and 6G communication systems using more proficient deep learning algorithms, which can help reduce power usage and hardware complexity issues.

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