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Channel reconstruction through improvised deep learning architecture for high-speed networks

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ABSTRACT

Efficient acquisition of channel state information (CSI) is quite complicated process but immensely essential to exploit probable benefits of massive multiple input multiple output (MIMO) systems. Therefore, a deep learning-based model is utilized to estimate channel feedback in a massive MIMO system. The proposed improvised deep learning-based channel estimation (IDLCE) model enhances channel reconstruction efficiency by using multiple convolutional layers and residual blocks. The proposed IDLCE model utilizes encoder network to compress CSI matrices where decoder network is used to downlink reconstruct CSI matrices. Here, an additional quantization block is incorporated to improve feedback reconstruction accuracy by reducing channel errors. A COST 2,100 model is adopted to analyse performance efficiency for both indoor and outdoor scenarios. Further, deep learning-based model is used to train thousands of parameter and correlation coefficients much faster and to minimize computational complexity. The proposed IDLCE model evaluate performance in terms of normalized mean square error (NMSE), correlation efficiency and reconstruction accuracy and compared against varied state-of-art-channel estimation techniques. Excellent performance results are obtained with large improvement in channel reconstruction accuracy.

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1. INTRODUCTION

Wireless communication networks have provided massive benefits to the society in the last few decades by persistently developing systems with higher throughput, higher flexibility, reliability, low latency and better coverage capacity. Additionally, tremendous efforts are given for the advancement of techniques like channel estimation, encoding, decoding, modulation, and demodulation. Thus, massive multiple input multiple output (MIMO) is one of the most promising and significant technology in a wireless communication network which is mainly utilized in fifth-generation (5G) cellular applications to enhance spectral efficiency and link capacity. Here, massive MIMO systems consists of multiple number of antennas at the base station (BS) and information obtained from the user equipment (UE) is reconstructed and serve multiple users [1]-[3] at low signal to noise ratio. Higher spectral efficiency is mainly depending on channel state information (CSI), which is acquired at BS by feedback back from UE. Thus, the potential benefits of massive MIMO systems are exploited by efficient acquisition of CSI and to improve bandwidth resource utilization. Moreover, high accuracy of CSI acquisition enhances performance efficiency.

Furthermore, another promising technique is cloud computing, which has massive impact on varied applications like communication, healthcare, manufacturing, banking, education and entertainment since last three decades. The utilization of cloud computing technology can provide maximum yield with its unique and highly beneficial features such as availability of numerous resources with on-demand and low-cost capabilities. The cloud computing technique mainly works on the principle of pay-per-use model and on-demand resource access. Another advantage of cloud computing technology is minimum management problems with multi-tasking abilities. Thus, the functionalities of cloud computing technology can help in finding novel technological solutions for mobile communication network in a communication and information technology field [4]. Thus, use of cloud computing technique and massive MIMO system can ensure efficiency enhancement of high bandwidth 5G mobile cellular network. Furthermore, these techniques can enhance flexibility and scalability of mobile cellular networks to fulfil the market expectations.

Furthermore, in case of uplink CSI medium, the estimation of CSI at BS is quite efficient due to the accurate transmission of pilot code words from the UE. However, current cellular systems mostly utilize uplink CSI estimation. Besides, the estimation of CSI in downlink CSI medium is quite challenging task, specifically in case of frequency division duplex (FDD) multiplexing. Whereas, downlink CSI estimation is achieved with the help of uplink CSI medium in time division duplex multiplexing using reciprocity [5]. However, downlink CSI estimation in FDD multiplexing using uplink CSI medium is quite complex task due to weak reciprocity. Furthermore, the approach utilized in classical MIMO systems produces massive overhead in which downlink CSI is estimated at UE with the help of pilot code words in FDD systems and after estimated CSI is fed back to the BS. However, in this approach, massive overhead is induced due to utilization of multiple antennas enhances dimensions of CSI matrices. Thus, this approach is infeasible in massive MIMO systems. Furthermore, channel overhead can be mitigated by efficient compression of CSI matrices. This can be achieved using compression sensing methods or deep learning techniques [6], [7].

Nevertheless, the sparsity of CSI feedback medium is exploited of a massive MIMO system using compression sensing based methods in a fixed domain [8]. Generally, compression sensing based approaches utilizes spatial-frequency domain to acquire CSI efficiently and CSI estimation is done based on the exploitation of spatial CSI correlation. Besides, spatial correlation is achieved by placing antennas closer to each other at BS in a massive MIMO system. However, in some literatures [9], joint sparsity of channel matrices is exploited based on the common local scatters. As a result, efficient compression of CSI matrices is achieved. However, optimization problem occurs at the time of decompression with computational complexity [7]. Thus, implementation of compression sensing based methods in real time and varied practical communication systems is quite challenging and difficult. However, deep learning-based approaches have observed tremendous growth in varied fields like wireless communication, computing, and signal processing [10], [11]. Furthermore, deep learning based approaches have shown tremendous performance in the field of image compression as well as better suited for CSI feedback mechanism. Further, the optimization problem of image reconstruction is efficiently handled using convolutional layers in deep learning based approaches. Besides, a mapping mechanism with residual network is utilized to refine estimated CSI matrices at the decoder side. Furthermore, high reconstruction accuracy is achieved using deep learning based approaches in terms of CSI feedback estimation. However, traditional approaches overlook the effect of quantization process. As a result, considerable errors can be generated in a practical communication system.

Therefore, in this article, an improvised deep learning-based channel estimation (IDLCE) model is proposed to estimate channel feedback and to mitigate CSI feedback overhead in a massive MIMO system. Further, CSI estimation and channel overhead reduction are done efficiently using proposed IDLCE model. The proposed model efficiently estimates CSI at UE and then fed back to BS. Moreover, a cloud platform is utilized to estimate CSI matrices and their accuracy in terms of normalized mean square error (NMSE) and correlation results between uplink and downlink channels. The proposed IDLCE model provide massive strength towards implementation of 5G wireless mobile network. The proposed IDLCE model improves bandwidth utilization as well as spectral efficiency. The proposed IDLCE model is utilized to exploit downlink CSI feedback medium based on the CSI estimated at the uplink medium at source and UE, respectively. Further, large training database is utilized to study channel feedback matrices using deep learning-based approach. The proposed IDLCE model provides better reconstruction accuracy and error reduction and compared against different CSI feedback approaches based on varied performance matrices such as NMSE and cosine similarity.

This paper is organised in following style. Section 2, describes about the related work demonstrated regarding massive MIMO system and the problems associate to it and solutions to sort those problems with the help of proposed IDLCE model. Section 3, discusses about the mathematical modelling utilized in proposed IDLCE for CSI feedback estimation. Section 4 describes about experimental results and their comparison against traditional CSI feedback approaches and section 5 concludes the paper.

2. RELATED WORK

Massive MIMO system is mainly utilized in 5G mobile cellular system and beyond applications. Here, BS in the massive MIMO system is equipped with multiple antennas and CSI reconstruction is acquired at UE and fed back to the BS. Thus, deep learning-based model is the best suitable approach for efficient CSI reconstruction. As a result, several researchers have provided their massive efforts to ensure an efficient CSI reconstruction technique using machine learning, cloud computing or deep learning methods. However, due to presence of channel errors, the reconstruction accuracy gets affected as well as traditional channel estimation techniques have high channel overhead. Thus, several researchers have provided their efforts in this domain to study the mentioned challenges and provide solutions to counter those problems.

According to Wei *et al.* [12], a low rank approximation-based compression model is presented to enhance CSI estimation accuracy in massive MIMO systems. Here, a CSI feedback method is adopted to improve CSI precision and channel overhead reduction efficiency. Furthermore, channel matrix characteristics are utilized to reconstruct CSI feedback and compression results are heavily improved. According to Choi *et al.* [13], a detailed investigation on channel matrices is conducted in Zero-Feedback FDD systems. The feasibility of frequency domain channel matrices is utilized to estimate parameters. Here, vector spatial signature (VSS) model is utilized to acquire channel data and to improve spectral efficiency by reducing NMSE errors. The performance is measured in terms of beamforming efficiency and NMSE. According to Ma *et al.* [14], a channel estimation and feedback mechanism is introduced using deep learning-based model to reduce the uplink pilot overhead in a millimetre-wave (mm-Wave) systems. This mechanism is utilized to jointly train the phase shift network and structured sparsity of channel is exploited to improve downlink channel estimation efficiency. According to Lee *et al.* [15], a downlink channel reconstruction technique is presented to handle Spatial Multiplexing in a massive MIMO system to improve uplink and downlink channel reciprocity. Here, downlink-based CSI reference signals are utilized to spectral efficiency and complexity issues. Simulation results are demonstrated in terms of spectral efficiency and channel reconstruction accuracy. According to Kim and Choi [16], a channel estimation technique is presented to counter channel errors in the mm-Wave massive MIMO systems. Here, analog-to-digital converters (ADCs) are used to estimate wide-band channel efficiency. Here, inter-user and inter-frame interference is mitigated based on the channel parameters and maximum a posteriori (MAP) criterion. According to Guo *et al.* [17], a compression sensing based model is introduced to compress and quantize CSI matrices in a convolutional neural network (CNN) based architecture in a massive MIMO system. Here, a novel training approach is adopted to reduce parameters by 38.0% and 46.7% and improve reconstruction accuracy. This technique outperforms traditional approaches in terms of parameter reduction and compression efficiency. According to Ye *et al.* [18], a deep learning-based model is adopted to de-noise channel matrices and improve reconstruction accuracy in massive MIMO systems. This technique enhances CSI feedback efficiency in a FDD domain. A perfect CSI feedback mechanism is adopted to compress CSI into a code word. According to Gkonis *et al.* [19], a detailed survey is presented on the challenges and feasibility of 5G wireless mobile networks by estimating CSI matrices in a massive MIMO system. This survey provides knowledge of hybrid analog-digital precoding mechanism, multiple access system, and wireless information.

Different views are presented in the mentioned literatures from various researchers about CSI feedback reconstruction using varied techniques like deep learning; CNN based model and massive MIMO and mm-Wave systems. However, still massive improvement is needed in terms of spectrum throughput, interference reduction, channel overhead and reconstruction accuracy. Thus, IDLCE model is introduced in this article to estimate CSI feedback reconstruction accuracy and channel overhead reduction. Further, cloud-computing technology is utilized to provide high channel accuracy results. Next section discusses about the mathematical modelling of IDLCE model.

3. MODELLING OF IDLCE

This section describes about the system modelling of proposed IDLCE model to estimate CSI feedback matrices in the massive MIMO system based on the improvised deep learning model with a quantization block. This technique enhances CSI feedback accuracy in a FDD multiplexing domain. Deep learning model is utilized to acquire channel data and to improve spectral efficiency by reducing NMSE errors. Previous work shows that a definite correlation present between uplink and downlink medium. Thus, utilization of uplink CSI matrices acquired in a FDD domain can possibly enhance the estimation efficiency of downlink CSI matrices. Here, Figure 1 demonstrates block diagram of proposed IDLCE model. Further, a detailed mathematical representation of proposed IDLCE model is presented in a following paragraph.

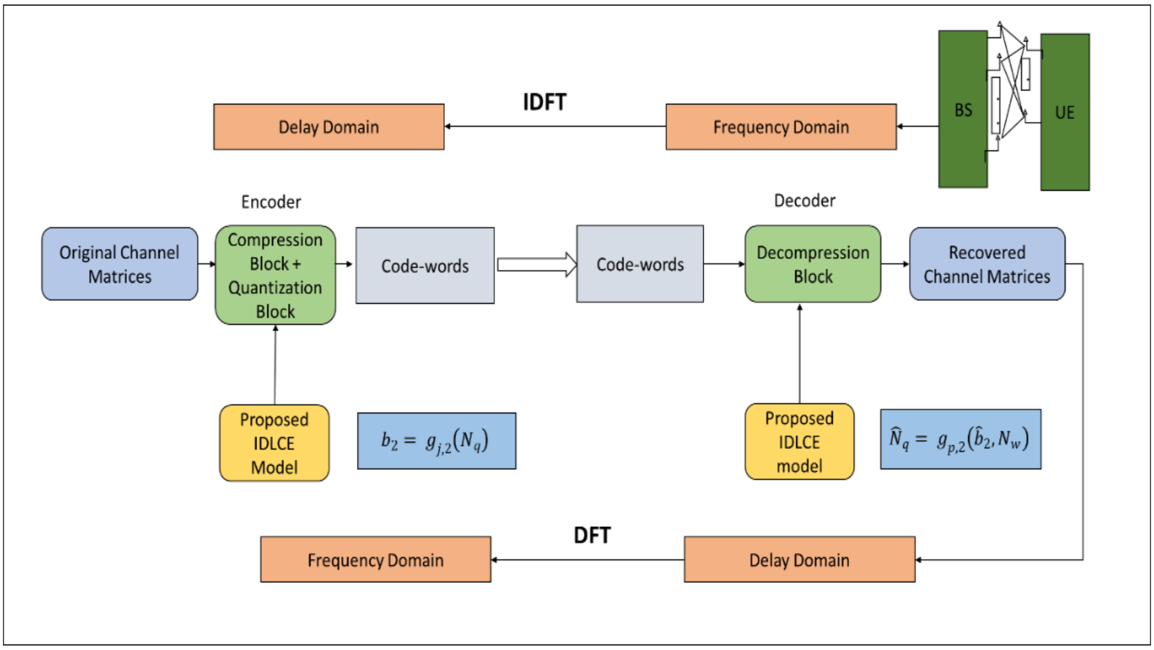

Figure 1. Block diagram of proposed IDLCE model

A massive MIMO system with a unitary cell is considered in which BS is equipped with several transmit antennas as $\mathrm{R_b} \gg 1$ whereas UE is equipped with a single receiver antenna. Here, orthogonal frequency division multiplexing (OFDM) is applied in a massive MIMO system using proposed IDLCE model over $\mathrm{R_g}$ subcarriers. Then, the code-word received in a downlink channel considering the $\mathrm{r-th}$ subcarrier is given by following (1).

$$l_q^{(r)} = n_q^{(r)^N} d_M^{(r)} z_q^{(r)} + x_q^{(r)} \tag{1}$$

Where, frequency response vector of a channel considering $\mathrm{r-th}$ subcarrier is denoted by $\mathrm{n_q^{(r)}}$ and channel vector $\mathrm{n_q^{(r)}}$ is proportional to $\mathbb{K}^{\mathrm{R_b}\times 1}$ and transmitted data code-word is denoted by $\mathrm{z_q^{(r)}} \in \mathbb{K}$. Further, precoding vector considering $\mathrm{r-th}$ subcarrier is expressed by $\mathrm{d_M^{(r)}} \in \mathbb{K}^{\mathrm{R_b}\times 1}$ whereas $\mathrm{x_q^{(r)}}$ and $(\cdot)^{\mathrm{N}}$ is expressed as additive interference or noise and conjugate transpose, respectively. Here, BS can evaluate precoding vector $\mathrm{d_M^{(r)}}$ with the help of channel vectors $\mathrm{n_q^{(r)}}$. Then, the code-word received in an uplink channel considering the $\mathrm{r-th}$ subcarrier is given by following (2).

$$l_w^{(r)} = d_P^{(r)^N} n_w^{(r)} z_w^{(r)} + d_P^{(r)^N} x_w^{(r)} \tag{2}$$

Where, frequency response vector of a channel considering $\mathrm{r-th}$ subcarrier is denoted by $\mathrm{n_w^{(r)}}$ and channel vector $\mathrm{n_w^{(r)}}$ is proportional to $\mathbb{K}^{\mathrm{R_b}\times 1}$ and received data code-word is denoted by $\mathrm{z_w^{(r)}} \in \mathbb{K}$. Further, received beam-former considering $\mathrm{r-th}$ subcarrier in an uplink medium is expressed by $\mathrm{d_P^{(r)}} \in \mathbb{K}^{\mathrm{R_b}\times 1}$ whereas $\mathrm{x_w^{(r)}}$ is expressed as added noise and $(\cdot)^{\mathrm{N}}$is a conjugate transpose, respectively. Here, BS can evaluate precoding vector $\mathrm{d_P^{(r)}}$ with the help of channel vectors $\mathrm{n_w^{(r)}}$ in an uplink medium. The downlink CSI matrices are represented in the matrix form in a spatial frequency domain using following (3).

$$\tilde{N}_q = \left[n_q^{(1)}, \ldots \ldots, n_q^{(R_g)}\right]^N \tag{3}$$

The uplink CSI matrices are represented in the matrix form in a spatial frequency domain using following (4).

$$\widetilde{N}_w = \left[n_w^{(1)}, \ldots \ldots, n_w^{(R_g)}\right]^N \quad (4)$$

Here, (3) and (4) is proportional to $\mathbb{K}^{R_g \times R_b}$, respectively. Here, downlink channel is estimated at UE in a FDD system and the estimated CSI is fed back to BS. Then, BS evaluates precoding vector $d_M^{(r)} \in \mathbb{K}^{R_b \times 1}$ with the help of this estimated downlink CSI feedback at BS. The feedback parameters utilized in a proposed massive MIMO system in numbers are given by $2R_bR_g$. However, these feedback parameters are directly proportional to the number of antennas. The utilization of excessive feedback parameters utilizes large bandwidth spectrum in a massive MIMO system. As a result, channel feedback overhead is greatly enhanced. Thus, channel overhead reduction is achieved by utilizing CSI sparsity in the delay domain. Furthermore, inverse discrete Fourier transform (IDFT) is used to get CSI matrices in angular-delay domain from the CSI matrices of spatial frequency domain, which can be expressed using following (5).

$$N_g G^N = N_m \quad (5)$$

Where, G is a DFT matrix with a singular row and is proportional to $G \in R_g \times R_g$ whereas G^N is an $R_g \times R_g$ IDFT unitary matrix, respectively. After IDFT applied in (3), most of the elements have almost zero-value due to the high sparsity of massive MIMO system in $R_b \times R_g$ channel matrix matrix N_m of the angular delay domain except first row V_g elements. Here, the elements of first row V_g has unique non-zero values. Thus, channel matrix rows get truncated into a single-row matrix directly. Thus, the downlink channel matrix N_q and uplink channel matrix N_w are denoted as $\widetilde{N}_q$ and $\widetilde{N}_w$ after IDFT process with a single row V_g distinct non-zero values, respectively. Furthermore, the code words are encoded to compress dimensions of downlink CSI matrices and low-bit encoding is performed. As a result, redundancy can be mitigated. Besides, the classical CSI methods utilizes only encoder-decoder mechanism, encoder is used to compress code words, and decoder is utilized to recover those code words, respectively. Thus, a quantizer block is added to the encoder system to jointly compress and quantize code words efficiently. Therefore, downlink CSI feedback medium in FDD system contains three blocks to reconstruct channel matrices such as encoder block, quantizer block and decoder block. Exactly, a DL-based channel estimation framework is designed to jointly compress dimensions efficiently and quantize CSI matrices at the receiver side. The reconstruction of code words is performed at the transmitter side to optimize CSI channel matrix reconstruction. Therefore, joint optimization of compression and quantization is performed using proposed IDLCE model in a massive MIMO system. Here, recovered downlink channel matrix is expressed by $\widehat{N}_q$ and $g_i(\cdot)$ denotes quantization function. Then, encoder block, quantizer block and decoder block using a proposed IDLCE model are expressed by following (6) to (8).

$$b_1 = g_{j,1}(N_q) \quad (6)$$

$$\hat{b}_1 = g_{i,1}(b_1) \quad (7)$$

$$\widehat{N}_q = g_{p,1}(\hat{b}_1) \quad (8)$$

Similarly, encoder block, quantizer block and decoder block using a proposed IDLCE model considering $\mathrm{DualNet} - \mathrm{IMag}$ architecture is expressed by following (9) to (11).

$$b_2 = g_{j,2}(N_q) \quad (9)$$

$$\hat{b}_2 = g_{i,2}(b_2) \quad (10)$$

$$\widehat{N}_q = g_{p,2}(\hat{b}_2, N_w) \quad (11)$$

Furthermore, the downlink CSI feedback channel matrix is optimized by minimizing $\left\|N_q - \widehat{N}_q\right\|^2$ and function $\|\cdot\|$ is represented as Frobenius normalization.

3.1. Deep learning-based channel state information feedback model

The proposed deep learning-based CSI feedback model achieves considerable performance gain and yield by reducing channel feedback overhead and enhancement of downlink CSI feedback reconstruction accuracy. Furthermore, potential benefits of encoder block are exploited to compress channel matrices and along with that, a quantization block is adopted to observe a drastic improvement in terms of compression accuracy in a massive MIMO system. Therefore, firstly, analysis of quantization effect on the length of code word is done to achieve high CSI reconstruction accuracy by using a generalized uniform quantizer. Further, a uniform quantizer is added with the compression block and the quantized CSI matrices are transmitted to the decoder block to observe quantization effect. Here, Figure 2 demonstrates a proposed deep learning-based CSI feedback model with a quantization block. The proposed deep learning-based CSI feedback architecture contains convolution layers and fully linked layers in an encoder network to compress dimensions of CSI matrices whereas decoder network contains fully linked layers and residual blocks to decompress code words and reconstruct downlink CSI channel matrices, respectively. Further, every residual block contains total number of three convolutional layers. Here, proposed multilayer (MLNet) architecture exploits the correlation of magnitude coefficients evaluated between uplink and downlink medium to enhance downlink CSI feedback accuracy as demonstrated in Figure 3. Furthermore, the proposed MLNet architecture perform phase and magnitude separation distinctly. Once phase and magnitude separation are performed, then correlated magnitude coefficients are transmitted to the encoder network at UE, which contains convolutional layers and fully linked layers. Then, the decoder network is utilized to receive compressed code words at the BS and CSI magnitude coefficients of uplink medium is utilized together with these received compressed code words. Then, fully linked layer is utilized to convert compressed code words into the original length of code words. Then, both CSI magnitude coefficients of uplink medium and downlink CSI coefficients are combined together using convolutional layers to compute output. Then, the obtained output is reformed into feature maps. Thus, the resultant feature maps are fed into the residual blocks to reconstruct downlink CSI matrices. Furthermore, a magnitude-phase quantization method is introduced to minimize bandwidth utilization with least quantization errors. Thus, the CSI magnitude coefficients with higher values provide greater phase quantization. Similarly, higher phase coefficients receive larger CSI magnitude values.

Furthermore, uniform quantization process is a simple and generalized rounding procedure and utilized in varied environments. Here, every value of channel coefficient is rounded to closest one using the rounding method with varied quantization levels. Then, the magnitude of CSI coefficients is normalized between are normalized between the intervals $[\mathrm{b_{max}}, \mathrm{b_{min}}]$. Consider that, number of bits are denoted as d in the process of magnitude normalization. Every magnitude value of CSI coefficient is quantized into 2^{d} levels in uniform manner using following (12) and (13).

$$\hat{b} = \Delta . \left\lfloor \frac{b}{\Delta} \right\rceil \tag{12}$$

Where,

$$\Delta = (\mathrm{b_{max}} - \mathrm{b_{min}}). \left(2^{\mathrm{d}} - 1\right)^{-1} \tag{13}$$

In this way, the uniform quantizer is integrated into the proposed deep learning-based CSI feedback model. In varied state-of-art-channel, estimation techniques provide channel feedback mechanism without any quantization approach. However, proposed IDLCE model obtain compressed CSI coefficients and then transmit the compressed and quantized CSI coefficients to the decoder network after quantization. Thus, the proposed IDLCE model is comparatively more robust than traditional channel estimation methods in terms of quantization errors. Finally, accuracy of CSI reconstruction process is much higher with quantization. As a result, feedback bandwidth efficiency gets enhanced.

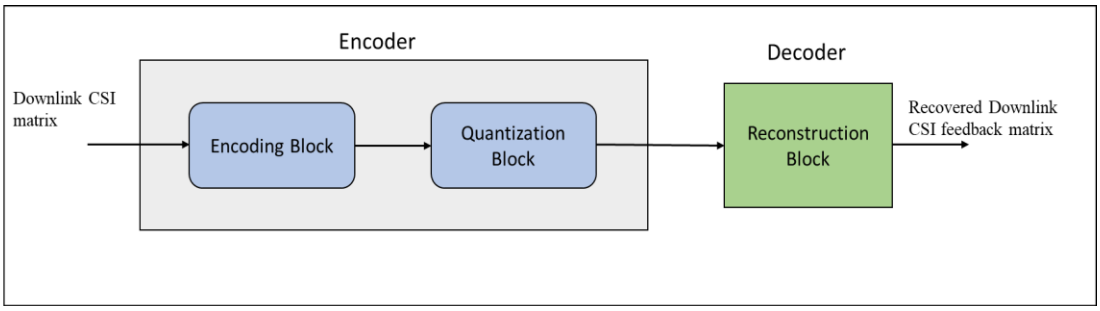

Figure 2. Quantization based proposed deep learning-based CSI feedback model

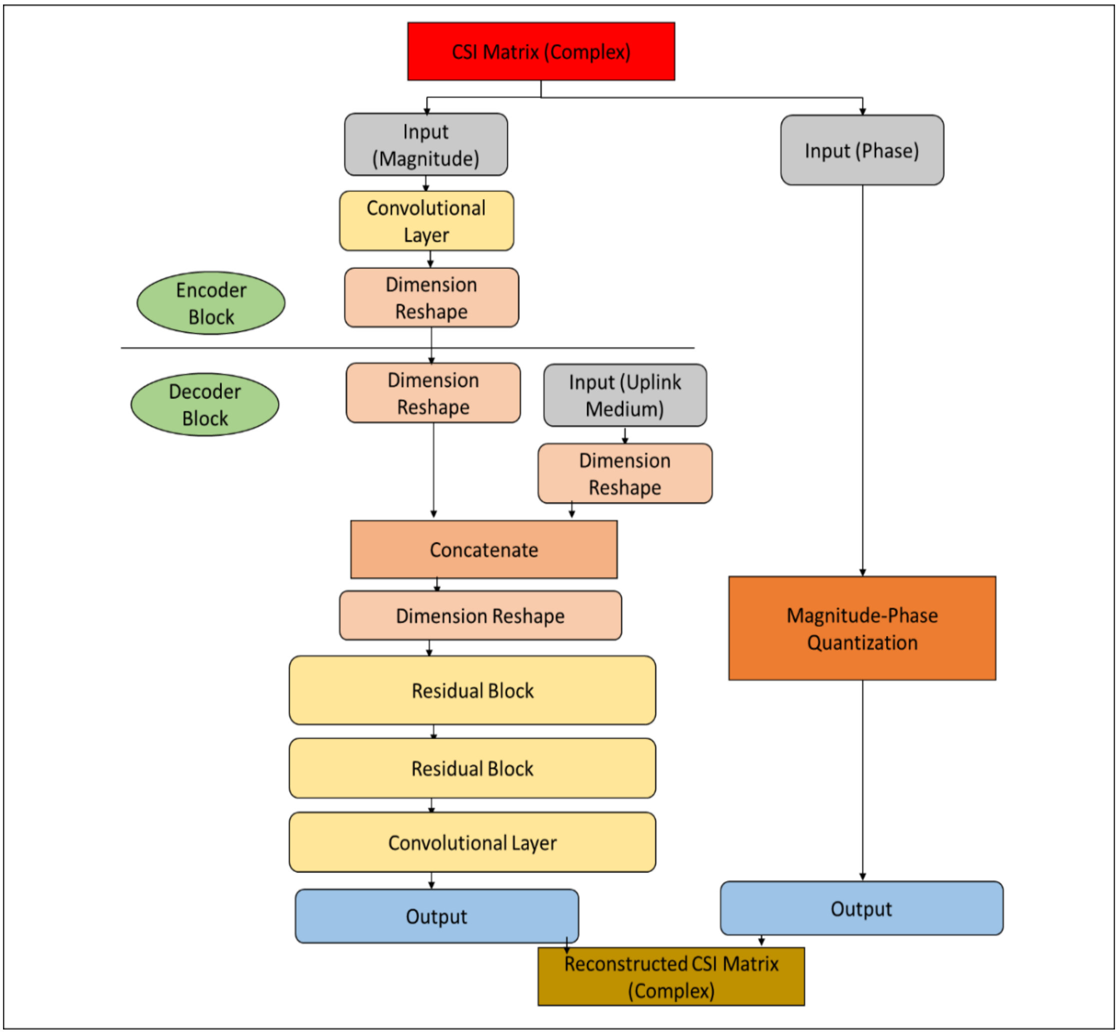

Figure 3. Architecture of proposed MLNET model

3.2. Correlation estimation using proposed improvised deep learning-based channel estimation model

The downlink CSI feedback matrices are estimated and channel feedback overhead is efficiently reduced using proposed IDLCE model. Here, deep learning-based model is introduced to enhance processing speed and parameter reduction. Here, real and imaginary parameters acquired from the correlation of downstream and upstream CSI matrices are controlled using proposed deep learning model. Further, the correlation coefficients are acquired in angular delay domain with the help of channel feedback matrices. Besides, due to the complex nature of correlation coefficients, they are separated into real and imaginary coefficients. However, obtained correlation coefficients are erratic for downlink and uplink channel matrices. Consider that phase exhibit lower correlation results than compare to the magnitude in angular-delay domain. Therefore, separate correlation of magnitude and phase coefficients are acquired.

Thus, the proposed IDLCE model fed back real and imaginary coefficients separately along with their signs. Further, proposed deep learning framework efficiently reduce channel overhead by sending uncorrelated data with their signs for uplink and downlink medium. An essential feature of the proposed IDLCE model is adoption of fully linker layers, residual blocks, convolutional layers and conversion into the feature maps. However, due to lesser values of correlated phase coefficients, compression of phase coefficients with their signs are performed at UE whereas magnitude coefficients of downlink medium and uplink CSI matrices are jointly optimized at the BS. This shows that the proposed IDLCE model ensure high performance accuracy and signal restoration efficiency.

4. PERFORMANCE EVALUATION

In this section, performance of proposed improvised deep learning-based channel estimation model is analyzed in a massive MIMO system to estimate high CSI feedback reconstruction and mitigate channel overhead. Here, deep learning model is adopted to train thousands of channel parameters and correlation coefficients efficiently. The proposed IDLE model lowers computational complexity by reduction in utilization of channel parameters. The acquired correlation coefficients are exploited by separating them into real and imaginary parts considering CSI matrices of uplink and downlink medium. Furthermore, Figure 3 demonstrates the architecture diagram of proposed MLNet model. It is clearly visible from the Figure 3 that CSI matrices are complex in nature in which phase and magnitude both parameters are separately fed and convolutional layers are utilized at encoder side to compress magnitude coefficients of CSI matrices as well as dimensions are reshaped using dimension reshape at encoder as well as decoder side. Further, both CSI matrices of uplink medium and magnitude coefficients of CSI matrices are concatenated after dimensions are reshaped. Then, convolutional layers and residual blocks are utilized to get output at the decoder side. Furthermore, magnitude-phase-quantization method is utilized to optimize phase coefficients into an output. Then, both the outputs are transformed into the reconstructed CSI matrices and these reconstructed output remains complex in nature. In this way, MLNet model is proposed to reconstruct CSI matrices. Also, correlation coefficients are evaluated by separating real and imaginary coefficients with their signs in angular delay domain. Furthermore, performance is evaluated in terms of NMSE in dB and correlation efficiency against compression ratio.

4.1. Dataset details

Here, a COST 2,100 model is utilized to assess performance efficiency of proposed IDLCE model in the massive MIMO system [20]. Furthermore, downlink CSI feedback reconstruction accuracy and correlation between uplink and downlink medium is also evaluated based on the data extracted for indoor and outdoor environments. Here, data of COST 2,100 model is segregated into indoor and outdoor environment. Further, indoor and outdoor environments are considered to evaluate performance of proposed CSI feedback model. Here, frequency is fixed at 5.1 GHz and 5.3 GHz for uplink medium and downlink medium considering indoor environment. Whereas, frequency is fixed at 260 MHz and 300 MHz for uplink medium and downlink medium considering outdoor environment. Here, multiple uniform linear array antennas are utilized in the massive MIMO system. Furthermore, BS is equipped with uniform linear array antennas $\mathrm{R_b} = 32$ and number of subcarriers used are $\mathrm{R_g} = 1{,}024$. Training of proposed IDLCE model is efficiently done using varied system parameters. Here, epoch size is 700 whereas batch size is 200. Rest of the simulation parameters are retained same as [20], [21]. Here, the performance of COST 2100 channel model is compared against varied classical CSI estimation techniques. The proposed deep learning model shows excellent performance in terms of channel parameter reduction as well as reconstruction efficiency. Furthermore, code-word reconstruction accuracy is evaluated in terms of NMSE and correlation similarity. The proposed IDLCE model enhances bandwidth utilization in the massive MIMO system to implement 5G cellular network efficiently.

4.2. Comparative study

The proposed IDLCE model evaluate performance in terms of NMSE, correlation efficiency and reconstruction accuracy and compared against varied state-of-art-channel estimation techniques. Table 1 demonstrates NMSE (dB) performance using proposed IDLCE model against varied state-of-art-channel estimation techniques such as CsiNet [22], BCsiNet [23], BACRNet-1, BACRNet-10, BACRNet-1 and BACRNet-10 [24] to estimate CSI feedback reconstruction accuracy. Table 1 results demonstrates superiority of proposed IDLCE model for indoor scenarios and outdoor scenarios. The proposed IDLCE model outperforms all the CsiNet and their versions in terms of error reduction efficiency against varied compression ratios. It is evident from Table 1 results that lower the compression ratio, the error reduction efficiency becomes higher. That means error reduction efficiency is inversely proportional to the compression ratio. However, channel estimation efficiency is significantly improved using proposed IDLCE model in a massive MIMO system. Furthermore, average improvement in channel reconstruction accuracy considering indoor scenario is observed as 34.90% against previous best CSI feedback method (BACRNet-10). Similarly, for outdoor scenarios, reconstruction accuracy improvement is observed as 53.90% against previous best CSI feedback method (BACRNet-10). As demonstrated in Table 1, the better performance results are highlighted in bold font.

Figure 4 shows a graphical representation of correlation performance using proposed IDLCE Model against varied compression ratios as 4, 8, 16, 32 and 64 to estimate correlation between CSI matrices of uplink and downlink medium considering indoor and outdoor scenarios. The proposed IDLCE model shows better results in terms of correlation efficiency against varied compression ratios such as 4, 8, 16, 32 and 64.

Figure 4 results shows that correlation results provide reasonably better performance for lower compression ratio.

Table 1. CSI reconstruction accuracy results against varied traditional channel estimation techniques

CR	Classical CSI methods	INDOOR	OUTDOOR
1/4	CsiNet	-17.36	-8.75
	BCsiNet	-17.25	-8.35
	BACRNet-1	-20.46	-9.3
	BACRNet-10	-23.36	-10.41
	BACRNet-1	-14.2	-7.03
	BACRNet-10	-17.27	-8.78
	Proposed IDLCE model	-28.98	-17.59
1/8	CsiNet	-12.7	-7.61
	BCsiNet	-12.39	-6.26
	BACRNet-1	-14.09	-6.82
	BACRNet-10	-17.47	-8.15
	BACRNet-1	-11.52	-5.52
	BACRNet-10	-14.96	-6.63
	Proposed IDLCE model	-19.47	-10.54
1/16	CsiNet	-8.65	-4.51
	BCsiNet	-8.99	-4.17
	BACRNet-1	-10.64	-4.65
	BACRNet-10	-12.88	-5.45
	BACRNet-1	-8.83	-2.92
	BACRNet-10	-11.7	-4.63
	Proposed IDLCE model	-16.47	-7.41

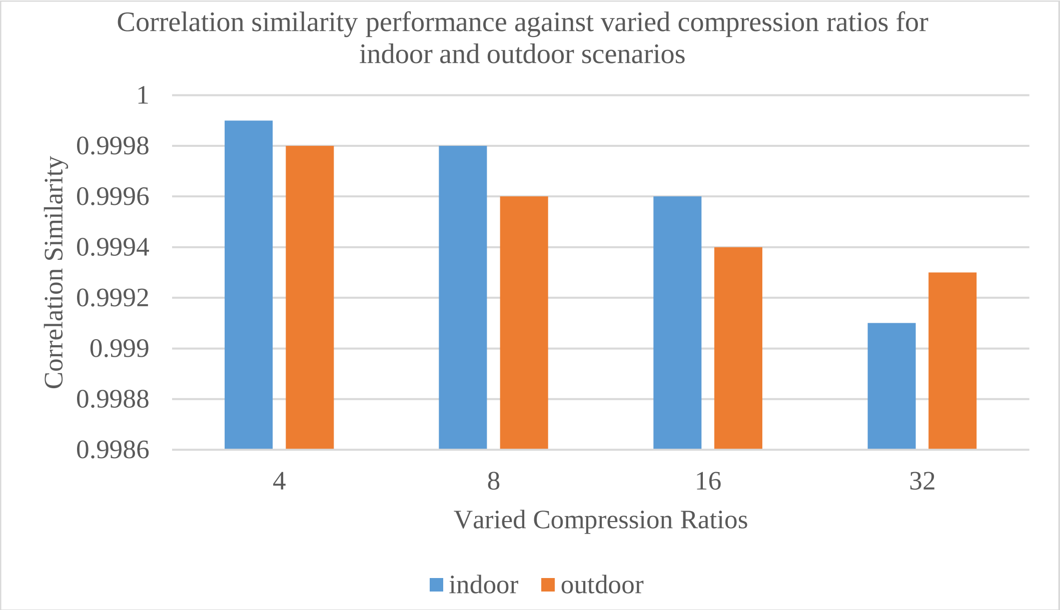

Figure 4. Correlation performance of proposed IDLCE model considering varied indoor and outdoor scenarios

Figure 5 demonstrates a graphical representation of channel feedback reconstruction accuracy using proposed IDLCE model against varied state-of-art-channel estimation techniques like LASSO [25], CSINet [22], CRNet-const [26], CRNet-cosine [26], DS-NLCsiNet [27], CLNet [28] and CsiFormer [21] to estimate downlink CSI feedback restoration efficiency considering indoor scenarios. The proposed IDLCE model outperforms all the channel estimation techniques in terms of channel feedback reconstruction efficiency against varied compression ratios such as 32 and 64. It is evident from Figure 5 results that NMSE results shows comparatively smoother performance when compression ratio is lower in indoor scenarios.

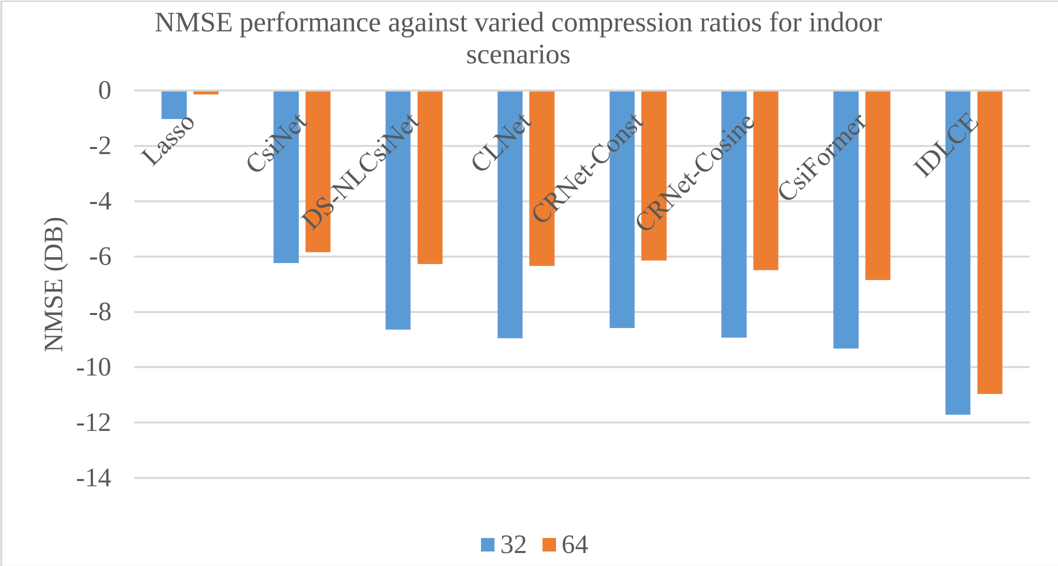

Figure 5. NMSE performance of proposed IDLCE model against varied state-of-art-channel estimation techniques considering indoor scenarios

Similarly, Figure 6 demonstrates a graphical representation of NMSE results for proposed IDLCE Model against different classical channel estimation techniques such as LASSO [25], CSINet [22], CRNet-const [26], CRNet-cosine [26], DS-NLCsiNet [27], CLNet [28] and CsiFormer [21] to estimate downlink CSI feedback reconstruction accuracy considering outdoor scenarios. The proposed IDLCE model outperforms all the classical CSI feedback methods in terms of channel reconstruction efficiency against varied compression ratios such as 32 and 64. It is evident from Figure 6 results that NMSE results shows comparatively smoother performance when compression ratio is lower considering outdoor scenarios.

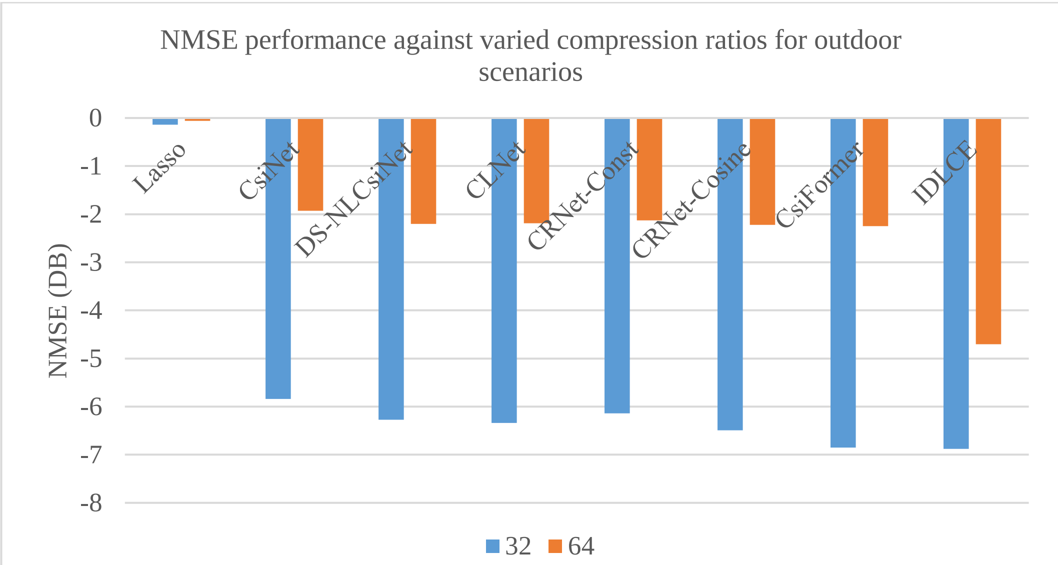

Figure 6. NMSE performance of proposed IDLCE model against varied state-of-art-channel estimation techniques considering outdoor scenarios

Table 2 demonstrates CSI reconstruction accuracy results in terms of NMSE reduction using proposed IDLCE model against classical CSI feedback estimation methods such as DS-NLCSiNet [27], CsiNetPlus [17] and ACRNet-1× [24] to estimate channel estimation accuracy. Table 2 results demonstrates superiority of proposed IDLCE model for both indoor and outdoor scenarios. The proposed IDLCE model outperforms both DS-NLCSiNet [27], CsiNetPlus [17] and ACRNet-1× [24] techniques in terms of error reduction results considering different compression ratios as 4, 8, and 16. It is evident from Table 2 results that lower the compression ratio, the error reduction efficiency becomes higher in both indoor and outdoor scenarios. However, a significant improvement is observed in terms of channel estimation efficiency using proposed IDLCE model in a massive MIMO system for both the scenarios. Furthermore, average improvement in terms of channel reconstruction accuracy considering indoor scenario is observed as 9.60% against previous best CSI feedback method (CsiNetPlus). Similarly, for outdoor scenarios, reconstruction accuracy improvement is observed as 47.09% against previous best CSI feedback method (CsiNetPlus). As demonstrated in Table 2, the better performance results are highlighted in bold font.

Table 2. NMSE performance of proposed IDLCE model considering varied state-of-art-channel estimation techniques considering indoor scenarios

	CR	DS-NLCsiNet	CsiNetPlus	ACRNet-1×	IDLCE
INDOOR	4	-24.99	-27.37	-27.16	-28.98
	8	-17	-18.29	-15.34	-19.47
	16	-12.93	-14.14	-10.36	-16.47
	4	-12.09	-12.4	-10.71	-17.59
OUTDOOR	8	-7.96	-8.72	-7.85	-10.54
	16	-4.98	-5.73	-5.19	-7.41

Similarly, Figure 7 shows channel reconstruction performance results evaluated using proposed IDLCE model against varied traditional CSI feedback methods such as CsiNet and CRNet [24] to estimate channel reconstruction efficiency and CSI feedback reduction considering both indoor and outdoor scenarios. The proposed IDLCE model provide superior results compare to classical channel estimation techniques against varied compression ratios such as 4, 8 and 16. It is evident from Figure 7 results that NMSE results shows comparatively better performance than any other state-of-art-CSI feedback estimation techniques.

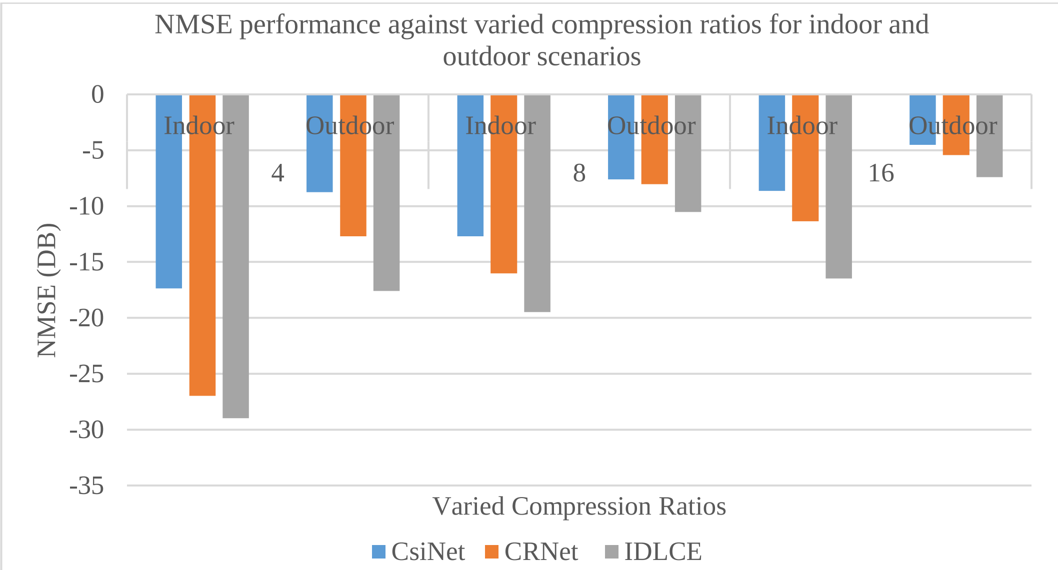

Figure 7. NMSE performance of proposed IDLCE Model considering indoor and outdoor scenarios

5. CONCLUSION

Massive MIMO has multiple potential benefits, which can improve bandwidth utilization and spectral efficiency of any wireless network. Thus, massive MIMO is a promising technology to efficiently implement fifth generation wireless cellular networks. Therefore, in this article, an IDLCE model is proposed. Here, the focus remains on an efficient extraction and reconstruction of downlink CSI feedback. A detailed mathematical modelling to estimate channel feedback and to reduce channel interference is discussed. Further, an encoder-quantizer-decoder model is presented to enhance spectral efficiency of massive MIMO systems. Additionally, the MLNet architecture is also presented to reconstruct CSI matrices and those obtained matrices remain complex in nature, which are further segregated into phase and magnitude coefficients. A COST 2,100 model is utilized to assess performance efficiency of proposed IDLCE model in the massive MIMO system. Performance results are carried out in terms of NMSE results and correlation efficiency against varied compression ratios. Here, average improvement in terms of channel reconstruction accuracy considering indoor and outdoor scenario is observed as 9.60% and 47.09% against CsiNet+method. Simulation results outperforms all the traditional channel estimation techniques for indoor and outdoor scenarios.

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