Estimating CSI for Future Generation MIMO Networks Using Deep Learning Techniques and its Applicability to Varied Environments

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Received: September 17, 2022; Accepted: December 8, 2022; Published: December 31, 2022

Abstract

Massive Multiple-Input Multiple-Output (MIMO) approach consists of high potential to achieve high data rate and one of the most favourable method to exploit channel feedback efficiency. Thus, a deep learning-based CSI feedback mechanism is proposed in this article to ensure high channel estimation efficiency with minimum CSI feedback overhead. Along with that, auto-encoders are adopted to study low dimensional representation of varied data structures. Moreover, CSI matrices are compressed at encoder side and recovered CSI matrices are obtained at decoder side. Further, convolution layers are utilized to get high quality features and fully linked layer is utilized to compress dimensions in CSI feedback matrices. The CSI feedback efficiency is enhanced using $\mathbf{DualNet-NCC}$ Architecture by exploiting magnitude correlation between downlink and uplink medium. Here, data of two varied environments such as indoor and outdoor cellular environment considering the Cost 2100 database is utilized and simulation is performed in cloud platform. An investigation is carried out to compare performance results of proposed DLAE model in terms of NMSE and correlation efficiency against varied traditional channel estimation approaches. Performance results shows higher channel estimation accuracy and spectral efficiency enhancement.

Keywords: Massive Multiple-Input Multiple-Output (MIMO), Channel State Information (CSI), and Deep Learning based Auto-Encoder (DLAE) Model, Cost 2100 Dataset, CSI Feedback Mechanism.

1 Introduction

Massive technological developments in a globalized communication system has caused large traffic demands across the globe and to accomplish those demands, current cellular systems are deployed within short distances almost everywhere. Additionally, wireless Local Area Networks (LAN) are deployed heavily at several places. Furthermore, expansion of novel ideas such as Machine to Machine (M2M) communication and Internet of Things (IoT) has heavily contributed to enhanced traffic demands along with mobile internet services. Moreover, global deployment of data offering from internet providers has facilities users to utilize mobile data services in daily life to an extreme level.

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 13, number: 4 (December), pp. 124-136. DOI: *10.58346/JOWUA.2022.I4.008*

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Massive Multiple-Input Multiple-Output (MIMO) is the most fascinating and prime technology to handle requirements of fifth generation mobile communication system [3-4]. Massive MIMO helps to achieve large data rates and enhances emitted energy efficiency. This technology is considered as the core technology to 5G cellular networks. Here, utilization of large antennas at Base station (BS) can help to achieve improved transmission capacity and deliver quality service uniformly throughout the cells in Massive MIMO based wireless communication systems. By using this technique, channel capacity also gets enhanced due to proper utilization of spatial diversity [5]. In massive MIMO, large information rate is achieved at user equipment (UE) and Channel State Information (CSI) is obtained at BS for every UE. Thus, massive MIMO is a vital wireless mechanism at the physical layer which is heavily responsible for higher bandwidth and providing high speed data facilities to several heterogeneous users simultaneously. However, efficiency of massive MIMO is immensely depending upon precise CSI estimation at BS. However, utilization of multiple antennas and larger bandwidth spectrum needed precise CSI prediction and acquisition so that a considerable amount of feedback is gained from every UE.

Downlink CSI feedback estimation can create varied challenges and complexities [6-7]. Furthermore, unwanted feedback estimation can cause extra consumption of UE power and spectrum bandwidth. Thus, many researchers have shown great interest in providing effective downlink CSI feedback estimation, compression and reconstruction.

Therefore, an investigation is carried out on downlink CSI feedback estimation in this article using Deep Learning based Auto Encoder (DLAE) model to reduce channel feedback overhead and enhance spectral efficiency. Here, impact of energy and optimized CSI matrices on proposed DLAE model are observed in a massive MIMO system. Moreover, auto-encoders are optimized to achieve high CSI feedback reconstruction efficiency by effectively training deep learning model. Here, Normalized Complex Coefficients (NCC) are utilized to separate energy from CSI matrices to provide objective functions of massive MIMO system. Moreover, distribution of network data and CSI feedback matrices are performed using proposed DLAE model so that reconstruct efficiency get enhanced. Here, correlation coefficients of bi-directional channel are exploited using $DualNet-NCC$ architecture. The adopted architecture is an improved version of $DualNet$ architecture. Simulation results are carried out using proposed DLAE model to get improved channel estimation efficiency and CSI feedback overhead reduction in a significant manner considering performance matrices such as Normalized Mean Square Error (NMSE), correlation factor and compression ratio.

This paper is organised in following mode. Section 2, describes regarding literatures presented to analyse Massive MIMO system and problems regarding Massive MIMO systems and solutions to this problem using the proposed Deep Learning-based Auto Encoder (DLAE) Model. Section 3, discusses about the methodology utilized in proposed DLAE for precise CSI estimation. Section 4 mentions about experimental results and their comparison with traditional CSI techniques and section 5 concludes the paper.

2 Related Work

Existing MIMO technology is extended as massive MIMO technology which is equipped with multiple (From hundreds to thousands) antennas connected to a BS to enhance network throughput and spectral efficiency. Moreover, mobile data speed and channel capacity get enhanced by bringing together radio nodes, antennas and bandwidth spectrum in massive MIMO [8-9] to access 5G cellular networks. Further, massive MIMO has potential to enhance spectral efficiency and throughput. This is a vital mechanism in a wireless communication system.

In [11], a channel estimation technique is presented to acquire imperfect Channel State Information (CSI) based on Deep Neural Networks in a Massive MIMO-OFDM Systems to achieve high accuracy results. Performance results are observed using deep neural network against conventional least square method which works on the interpolation process. In [12], a novel CSI feedback mitigation method is introduced to compress CSI feedback based on Randomized Low-Rank Approximation. This method provides high precision accuracy results and reduces computational complexity. Here, a large channel matrix is utilized to obtain error free CSI reconstruction. In [13], a Lightweight Convolutional Neural Networks architecture is designed to reconstruct CSI feedback matrices and reduce channel overhead in massive MIMO. Moreover, a deep learning-based network is designed to reduce computational complexity and enhance reconstruction efficiency. In [14], a zero-feedback FDD massive MIMO system is introduced to explore channel dimensions in frequency domain. Moreover, a detailed investigation is carried out on channel extrapolation based on generalized expectation-maximization parameters. Here, channel data is acquired to evaluate beamforming efficiency, mean squared error and spectral efficiency. In [15], a channel estimation and feedback mechanism is adopted based on deep learning framework in a Millimetre-Wave Massive MIMO System with hybrid beamforming. A model driven method is utilized to exploit channel sparsity. Here, high-dimensional channel estimation is obtained to mitigate uplink overhead. Moreover, a priori and learning model is presented to enhance feedback reconstruction performance based on vectors learned approximate message passing. In [16], a channel estimation approach is adopted to exploit the channel sparsity in a Massive MIMO system. Along with that, hybrid transceivers are utilized to limit the information loss. Here, region-specific measurement matrix is used to improve the signal measurement efficiency. This technique shows high performance results in terms of computational complexity and spectral efficiency. In [17], a spatial multiplexing scheme is utilized to reconstruct downlink channel feedback in a Massive MIMO System. Here, critical channel state information (CSI) is acquired in a time division duplexing (TDD) based on reference and training signals. Here, downlink CSI overhead is reduced using CSI reconstruction technique. In [18], a channel estimation technique is presented in a mm-Wave Massive MIMO Systems to mitigate inter-user interferences. Here, analog to digital convertors are utilized to reduce propagation delay. In addition, greedy selection-cross validation-based algorithm is adopted to get minimum mean square error (MSE).

3 Modelling of Proposed Deep Learning based Auto Encoder (DLAE) Model

In this section, a mathematical modelling of proposed deep learning based auto encoder (DLAE) model is introduced to improve CSI feedback estimation efficiency and mitigate CSI feedback overhead. Here, the proposed DLAE model enhances spectral efficiency with the help of Normalized Complex Coefficients (NCC) and provide high quality compression of CSI matrices. Furthermore, normalized mean square errors (NMSE) are eliminated using NCC supported $DualNet$ architecture. There are two types of CSI feedback designs are discussed in this article. First design provides information about downlink CSI feedback and second design gives information about uplink medium supported downlink CSI feedback. Here, encoder and decoders are utilized to reconstruct CSI feedback matrices. Here, NCC supported CSI feedback design is segregated into matrix of CSI feedback which are supported by normalized complex conjugates and energy factor. Figure 1 demonstrates architecture of NCC supported downlink during CSI Feedback.

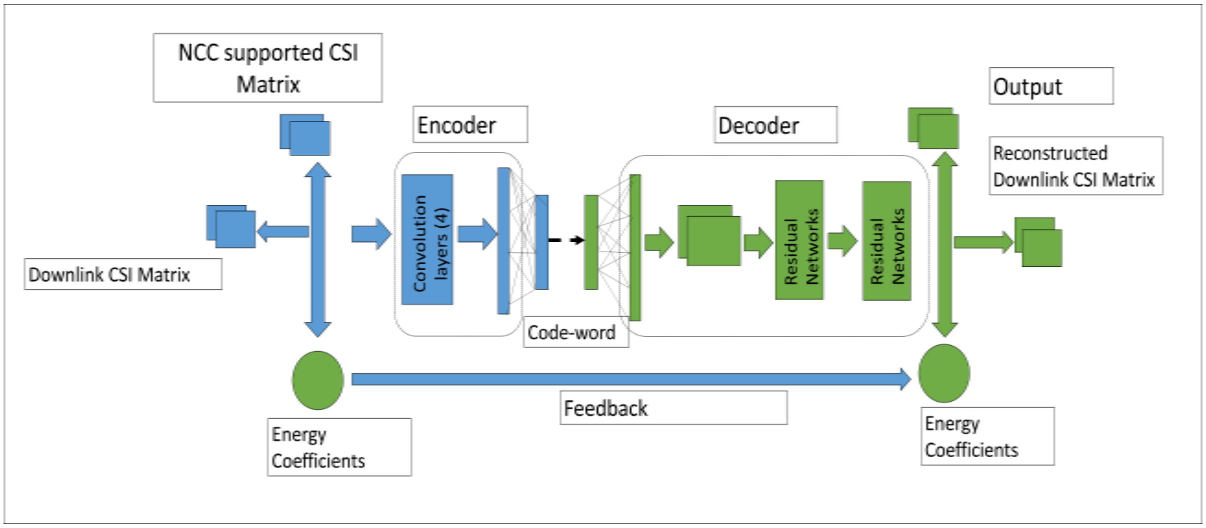

Figure 1: Architecture of NCC Supported Downlink CSI Feedback System

In this article, a massive MIMO system is presented with a unitary cell where the broadcaster station (BS) consist of more than one antennas as $P_d \gg 1$ and a single antenna is placed at every User Equipment (UE). For P_a subcarriers, orthogonal frequency division multiplexing (OFDM) is utilized and received code-word of downlink medium is given by following expression at the $j-th$ subcarrier,

$$m_{g,j} = q_{g,j}^{Q} r_{s,j} t_{g,j} + k_{g,j}, \quad (1)$$

Where, channel vector considering the $j-th$ subcarrier is expressed as $q_{g,j} \in \mathbb{L}^{P_d \times 1}$ for downlink medium and precoding vector of transmission is given by $r_{s,j} \in \mathbb{L}^{P_d \times 1}$ and the amount of noise added in the system is given by $k_{g,j} \in \mathbb{L}$ and the code-word transmission is expressed by $t_{g,j} \in \mathbb{L}$ and transpose of complex conjugates is expressed as $(\cdot)^Q$. Moreover, received code-word of uplink medium is given by following expression at the $j-th$ subcarrier,

$$m_{w,j} = r_{y,j}^{Q} q_{y,j} t_{y,j} + r_{y,j}^{Q} a_{y,j}, \quad (2)$$

Where, precoding vector of reception is given by $r_{y,j} \in \mathbb{L}^{P_d \times 1}$ and the amount of noise added in the system is given by $a_{y,j} \in \mathbb{L}$ and channel vector considering the $j-th$ subcarrier is expressed as $q_{w,j} \in \mathbb{L}^{P_d \times 1}$ for uplink medium and the code-word reception is expressed by $t_{g,j} \in \mathbb{L}$. Here, CSI matrices of uplink medium in a frequency domain is given by $\tilde{Q}_w = [q_{w,1}, \ldots \ldots, q_{g,P_a}]^Q$ and CSI matrices of downlink medium in a frequency domain is given by $\tilde{Q}_g = [q_{g,1}, \ldots \ldots, q_{g,P_a}]^Q$ which belongs to $\mathbb{L}^{P_a \times P_d}$. Moreover, broadcaster station can determine precoding vector for transmission in every subcarrier considering channel matrix of downlink medium $\tilde{Q}_g$. Further, the CSI matrix size of downlink medium belongs to $\mathbb{L}^{P_d \times P_a}$. As a result, overhead of CSI feedback becomes large in a massive MIMO system. So that, to mitigate this feedback payload, sparsity of CSI matrices is exploited in a time domain. There are multiple paths to transmit code-words with some delay. Thus, CSI matrix considering frequency domain Q_a is converted into CSI matrix of time domain as Q_s using Inverse Discrete Fourier Transform (IDFT) and expressed by following equation.

$$A^Q Q_a = Q_s \quad (3)$$

Where, A shows a $P_a \times P_a$ singular DFT matrix and similarly, A^Q shows a $P_a \times P_a$ singular IDFT matrix. Here, the $P_d \times P_a$ CSI matrix Q_s obtained from IDFT of CSI matrix Q_a, contain all the elements as nearly zero except the elements of first-row Y_g. Here, only first row elements are non-zero.

Thus, all the rows of CSI matrix, get discarded except the first row Y_g elements. Thus, the obtained channel matrix consists of singular row and having varied non-zero elements. Moreover, Q_g is obtained from the IDFT of $\tilde{Q}_g$ and Q_w is obtained from the IDFT of $\tilde{Q}_w$ which consist of a singular row Y_g. Here, after estimation of Q_g and Q_w for downlink and uplink medium, respectively, compression process can be performed. Then, the proposed DLAE model, is utilized to mitigate redundancy in downlink and Uplink CSI matrices at the UE. Here, two forms of CSI feedback designs are presented in this article. One form is named as downlink CSI feedback design and other form is named as downlink CSI feedback design supported by uplink medium. Then, recovered CSI matrix considering downlink medium is given by $\hat{Q}_g$. The encoding function is represented as $a_h(\cdot)$ and decoding function is represented as $a_g(\cdot)$. Thus, encoding and decoding functions, considering downlink CSI feedback design are represented by following equations as,

$$c_1 = a_{h,1}(Q_g), \quad (4)$$

$$\hat{Q}_g = a_{g,1}(c_1) \quad (5)$$

Moreover, encoding and decoding functions, considering downlink CSI feedback design are represented by following equations as,

$$c_2 = a_{h,2}(Q_g), \quad (6)$$

$$\hat{Q}_g = a_{g,2}(c_2, Q_w) \quad (7)$$

3.1 Normalized Complex Coefficients (NCC) Supported CSI Feedback using Proposed DLAE Model

CSI feedback design supported by normalized complex coefficients and this NCC supported CSI feedback matrices are obtained with the help of proposed DLAE model. Furthermore, deep learning model is an efficient mechanism to train large dataset structures and mostly utilized in computer and signal processing applications. Besides, DL model is widely utilized in massive MIMO systems for downlink CSI feedback estimation [19] and low rate channel estimation [20-21] while handling limitations of state-of-art-channel estimation techniques effectively.

Besides, at the time of channel matrix feature scaling, there is a chance of path loss occurrence which can heavily impact the performance of proposed DLAE model. Thus, this path loss is managed using data distribution model. There is a lot of difference between image data distribution and distribution of CSI feedback matrices. While handling image data distribution, magnitude order of all the image pixel remains similar. However, distribution of CSI feedback matrices possesses a lot of data and due to proportionality of path loss towards the distance between BS to UE, causes large amount of data in terms of magnitude order. A massive difference is detected between CSI feedback matrices obtained at UE close to BS and CSI feedback matrices obtained at UE far from BS. While comparing both CSI feedback obtained at UE, it is observed that the proposed DLAE model is rather less delicate to CSI feedback obtained far from BS. However, data distribution model is used in state-of-art-channel estimation methods, is mainly adopted in image processing applications. Thus, path loss occurs due to insufficient DL training and that loss is stated as Mean Square Error (MSE). Thus, MSE is defined by following equation.

$$\rho = (k)^{-1} \sum_{b=1}^{k} \left\| Q_g^b - \hat{Q}_g^b \right\|^2 \quad (8)$$

Where, MSE is expressed by ρ and database sample index is given by b. Further, the function $\|\cdot\|$ represents Frobenius normalization. Then, Normalized Mean Square Error (MSE) is given by following equation.

$$\delta = (k)^{-1} \sum_{b=1}^{k} \frac{\left\|Q_g^b - \hat{Q}_g^b\right\|^2}{\left\|Q_g^b\right\|^2} \quad (9)$$

Here, NMSE is one of the key performance metrics to determine channel estimation accuracy and feedback efficiency. Further, MSE is treated as a loss function so the proposed DLAE model focuses more on the matrices with higher energy. Besides, a Normalized Complex Coefficients (NCC) supported CSI feedback design is proposed to handle these mentioned issues with the help of proposed DLAE model. Hence, the NCC supported CSI feedback design breaks down CSI matrix of downlink medium Q_g^binto two parts in which first part represents energy matrices f_b and remaining part defines NCC supported CSI feedback matrix as $\check{Q}_g^b$. Here, energy coefficients of CSI matrices are given by $f_b = \left\|Q_g^b\right\|$ and NCC supported CSI feedback matrix is represented as,

$$\check{Q}_g^b = Q_g^b . \left\|Q_g^b\right\|^{-1} \quad (10)$$

Here, original CSI matrix is separates into two type of matrices in which energy coefficients of CSI matrix and NCC supported CSI feedback matrix are fed back distinctly. The proposed NCC supported CSI feedback design has varied benefits in which first is optimization of loss function and effective CSI reconstruction by minimizing loss function as,

$$\begin{aligned} I_\delta &= (k)^{-1} \sum_{b=1}^{k} \left\|\check{Q}_g^b - \hat{\check{Q}}_g^b\right\|^2 \\ &= (k)^{-1} \sum_{b=1}^{k} \left\|Q_g^b / \left\|Q_g^b\right\|^2 - \hat{Q}_g^b / \left\|Q_g^b\right\|\right\|^2, \quad (11) \\ &= (k)^{-1} \sum_{b=1}^{k} \left\|Q_g^b - \hat{Q}_g^b\right\|^2 / \left\|Q_g^b\right\|^2 \end{aligned}$$

Therefore, efficient training is performed to minimize NMSE using proposed DLAE model by eliminating loss function. Further, another benefit is separation of energy coefficients from CSI feedback matrices using proposed DLAE model. The magnitude order of recovered CSI matrices are similar as the input CSI matrices fed into the proposed DLAE model. This shows that efficient channel estimation is performed by normalizing variety of gradient features and due to loss function minimization, channel feedback overhead is reduced and speed of the network get increased. Therefore, proposed DLAE model enhances channel capacity in an effective manner with high compression efficiency.

3.2 Normalized Complex Coefficients Supported $DualNet - NCC$ Architecture

The proposed DLAE model utilizes $DualNet - NCC$ Architecture which is supported by normalized complex coefficients. The CSI feedback efficiency is enhanced using $DualNet - NCC$ Architecture by exploiting magnitude correlation between downlink and uplink medium. Besides, the adopted $DualNet - NCC$ Architecture performs better in terms of reconstruction efficiency than $DualNet - MAG$ Architecture using channel correlation coefficients. Here, performance is enhanced by encoder and decoder mechanism. Here, signal interference is reduced to train auto-encoders efficiently based on the energy coefficients isolated from downlink CSI matrix. Here, magnitude of CSI matrices as well as phase of CSI matrices are distinctly encoded by exploiting downlink and uplink channel correlation and fed back to CSI feedback mechanism. Once the phase and magnitude get separated, the CSI magnitudes are utilized to input into the encoder mechanism to compress dimensions whereas CSI magnitudes of uplink medium are used in the decoder mechanism to reconstruct downlink CSI matrices.

Here, downlink CSI matrices are recovered using encoded code-words. Here, as mentioned before, convolution layers are utilized to get high quality features and fully linked layer is utilized to compress dimensions. Firstly, the encoded code-words are mapped into a fixed length using a fully linked layer. Then, the CSI matrices of uplink medium are reformed into a vector quantity and concatenated with the code-words which are decompressed. Once this concatenation is done, the output is reformed into two feature maps to recover downlink CSI matrices. Furthermore, poor phase correlation is observed in traditional channel estimation approaches and feedback bandwidth can be wasted which can be avoided by quantizing phase of downlink CSI matrices and fed to encoder mechanism to get finer phase. At last, all the magnitudes are joined together with their respective phases to reconstruct complex conjugates-based CSI matrices. Then, energy coefficients are joined with recovered complex conjugates-based CSI matrices to get fully reconstruct CSI matrices.

Simulation results are analyzed and obtained using the proposed DLAE model. Here, performance accuracy is evaluated and compared against various state-of-art channel estimation techniques in terms of NMSE and correlation efficiency results. In this article, main focus remains on the channel feedback efficiency enhancement by improving spectral efficiency and removing CSI overhead in a massive MIMO system. Here, energy get separated from downlink CSI matrices using Normalized Complex Coefficients (NCC). Moreover, $DualNet - NCC$ architecture is presented to exploit magnitude correlation coefficients between downlink and uplink medium. In this article, NCC supported downlink CSI feedback architecture is demonstrated to provide high quality compression of CSI matrices. Here, auto-encoders are utilized to investigate low dimensional representation of highly trained dataset whereas deep learning model is utilized to train large data structures and to improve performance gain. Here, simulation results are obtained using a Google CoLab Platform and simulation code is structured in Python language. Here, the proposed DLAE model is simulated on the $INTEL\,(R)$ core $(TM)\,i5 - 4460$ processor with $16\,GB\,RAM$ and It has 64-bit windows 10 OS with 3.20 $GHz\,CPU$.

3.3 Dataset Details

In this section, a detailed information is carried out on the Cost 2100 database. Here, data of two varied environments are obtained considering the Cost 2100 database. These two environments are indoor cellular environment and outdoor cellular environment. The data in indoor environment is carried out at a frequency 5.3 GHz whereas the data of outdoor environment is acquired at a frequency 300 GHz. The proposed DLAE model contains total number of $P_d = 32$ antennas equipped at broadcaster station (BS). The type of antennas utilized in this system are uniform linear array antennas. The model contains total number of subcarriers $P_a = 1024$ at BS. Furthermore, CSI feedback matrix Q_a is converted from frequency domain to delay domain CSI matrices Q_s with the help of IDFT. Further, matrix Q_s is truncated into a single row matrix which consists of all non-zero elements and other all the rows which contains zero value elements are discarded. Besides, step size is 500 and iterates for all 90 epochs whereas convolution output size is 32. Furthermore, experimental parameters are adopted in the proposed DLAE model are represented in Table 1 to analyse correlation efficiency and NMSE results.

Table 1: Simulation Parameters Adopted in Proposed DLAE Model

Frequency (GHz)	5.3
Number of Subcarriers (Q_d)	1024
Number of Antennas (Q_a)	32
Convolution output size	32
Step size	500
Total number of epochs	90
Residual Blocks	2
Batch Size	200
Training Samples	100000
Testing Samples	20000

3.4 Comparative Study

In this section, an investigation is carried out to compare performance results of proposed DLAE model in terms of NMSE and correlation efficiency against varied traditional channel estimation approaches. Moreover, the efficiency is determined using proposed DLAE based CSI matrices by evaluating NMSE. This NMSE results are obtained between real CSI matrices and reconstructed CSI matrices. Moreover, convolution layers are adopted to improve performance gain and optimization accuracy. The proposed DLAE model generate high quality features from downlink CSI matrices. Further, Table 2 shows performance results considering performance matrices such as NMSE for outdoor and indoor environments against varied CSI reconstruction approaches. Moreover, the performance of NMSE is carried out considering compression ratios as 1/32 and 1/64 respectively. Besides, the proposed DLAE model is compared against several CSI methods such as LASSO [24], $CSINet$ [22], $DS-NLCsiNet$ [26], $CLNet$ [27], Csi Former [28], $CRNet-Const$ [25] and CR Net-cosine [25] considering performance metric as NMSE. The performance results verify that the accuracy of proposed DLAE model is much better than traditional CSI reconstruction methods. The bold letters in Table 2 results show the best performance results. The CSI reconstruction accuracy is enhanced by 32.64% for compression ratio as 1/64 and enhancement is achieved as 33.79% for compression ratio as 1/32 against $CsiFormer$ considering indoor cellular environment. Whereas, the CSI reconstruction accuracy is enhanced by 118.2% for compression ratio as 1/64 and enhancement is achieved as 86.10% for compression ratio as 1/32 against $CsiFormer$ considering outdoor cellular environment. Therefore, the ultimate network performance is enhanced with the help of downlink CSI matrices supported by normalized complex coefficients. Furthermore, Table 3 provides details of performance results in terms of correlation similarity and NMSE using proposed DLAE model. It is evident from performance results that accuracy is much higher using proposed DLAE based CSI reconstruction model. Furthermore, efficiency using $DualNet-NCC$ architecture is quite high.

Table 2: NMSE (dB) Comparisons using Proposed DLAE Model Against Varied CSI Methods

7	Methods	Indoor	Outdoor
		NMSE (dB)	
1/32	$LASSO$	-1.03	-0.24
	$CSINet$	-6.24	-2.81
	$DS-NLCsiNet$	-8.64	-3.35
	$CLNet$	-8.95	-3.49
	$CRNet-Const$	-8.58	-3.19
	$CRNet-cosine$	-8.93	-3.51
	$CsiFormer$	-9.32	-3.51
	$\boldsymbol{DLAE}$	**-12.47**	**-6.55**
1/64	$LASSO$	-0.14	-0.06
	$CSINet$	-5.84	-1.93
	$DS-NLCsiNet$	-6.27	-2.20
	$CLNet$	-6.34	-2.19
	$CRNet-Const$	-6.14	-2.13
	$CRNet-cosine$	-6.49	-2.22
	$CsiFormer$	-6.85	-2.25
	$\boldsymbol{DLAE}$	**-9.10**	**-4.91**

Here, Table 3 demonstrates NMSE (dB) results for input and output scenarios using proposed DLCSI model. Here, simulation results are carried out using varied compression ratios and both NMSE and correlation similarity index shows superior results.

Furthermore, Table 4 demonstrates the comparison of proposed DLAE model with varied classical CSI feedback systems. The performance is compared against different CSI feedback methods as CsiNet [20], CRNet [25], DS-NLCsiNet [26], CsiNetPlus [29], ACRNet-1×, ACRNet-10× and ACRNet-20× [30] considering different compression ratio. Here, only those techniques are adopted to compare with proposed DLAE model which perform much better than traditional CSI estimation methods. Further, it is evident from performance results that proposed DLAE model outperforms all the classical CSI feedback estimation methods. Besides, ACRNet-10× and ACRNet-20× shows decent performance and reconstruction results. However, proposed DLAE model performs better than those techniques by quite some extent in terms of NMSE for both indoor and outdoor cellular environments. The CSI compression accuracy is improved by 4.27%, 10.34% and 11.69% for compression ratio as 1/4, 1/8 and 1/16 against previous best compression method ACRNet-20× [30] considering indoor cellular environment, respectively. Whereas, CSI compression accuracy is improved by 17.12%, 20.04% and 34.01% for compression ratio as 1/4, 1/8 and 1/16 against previous best compression method ACRNet-20× [30] considering outdoor cellular environment. This shows superiority of proposed DLAE model in terms of NMSE and correlation similarity.

Table 3: NMSE (dB) for Input and Output Scenarios Using Proposed DLCSI Model

Compression Ratio	Indoor	Outdoor
	NMSE (dB)	
1/4	-33.39	-16.699
1/8	-22.9304	-11.6252
1/16	-16.8119	-8.65716
1/32	-12.4708	-6.55133
1/64	-9.10358	-4.91791

Table 4: NMSE (DB) Comparison between Series of Feedback Networks and Proposed DLAE Model

CR	Classical CSI Methods	INDOOR	OUTDOOR
1/4	Csi Net [20]	-17.36	-8.75
	CR Net [25]	-26.99	-12.7
	DS-NL Csi Net [26]	-24.99	-12.09
	Csi Net Plus [29]	-27.37	-12.4
	ACRNet-1 × [30]	-27.16	-10.71
	ACRNet-10 × [30]	-29.83	-13.61
	ACRNet-20 × [30]	-32.02	-14.25
	Proposed DLAE Model	**-33.39**	**-16.69**
1/8	Csi Net [20]	-12.7	-7.61
	CR Net [25]	-16.01	-8.04
	DS-NL Csi Net [26]	-17	-7.96
	Csi Net Plus [29]	-18.29	-8.72
	ACRNet-1 × [30]	-15.34	-7.85
	ACRNet-10 × [30]	-19.75	-9.22
	ACRNet-20 × [30]	-20.78	-9.68
	Proposed DLAE Model	**-22.93**	**-11.62**
1/16	Csi Net [20]	-8.65	-4.51
	CR Net [25]	-11.35	-5.44
	DS-NL Csi Net [26]	-12.93	-4.98
	Csi Net Plus [29]	-14.14	-5.73
	ACRNet-1 × [30]	-10.36	-5.19
	ACRNet-10 × [30]	-14.32	-6.3
	ACRNet-20 × [30]	-15.05	-6.47
	Proposed DLAE Model	**-16.81**	**-8.65**

Moreover, graphical representation of performance comparison is presented considering varied CSI reconstruction techniques such as CsiNet, BCsiNet, BACRNet-1x, BACRNet-10x, BACRNet-1x, BACRNet-10x [30] against proposed DAAE model. Here, Figure 2 demonstrates CSI reconstruction performance results using proposed DLAE model and compared against varied CSI reconstruction methods considering indoor scenarios for varied compression ratios as 1/4, 1/8 and 1/16. Similarly, Figure 2 demonstrates CSI reconstruction performance results using proposed DLAE model and compared against varied CSI reconstruction methods considering outdoor scenarios for varied compression ratios as 1/4, 1/8 and 1/16. It is evident from graphical performance results that proposed DLAE model shows better reconstruction accuracy than any other state-of-art- CSI reconstruction considering both indoor and outdoor cellular scenarios.

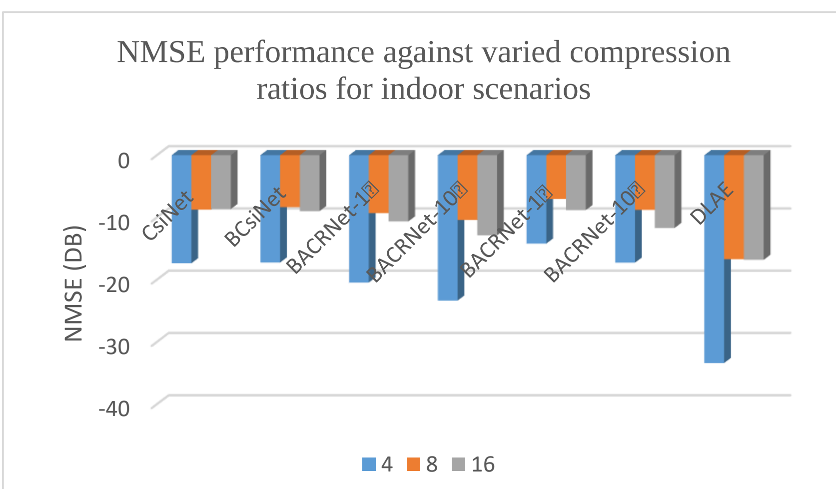

Figure 2: CSI Reconstruction Performance Results Using Proposed DLAE Model and Compared Against Varied CSI Reconstruction Methods Considering Indoor Scenarios

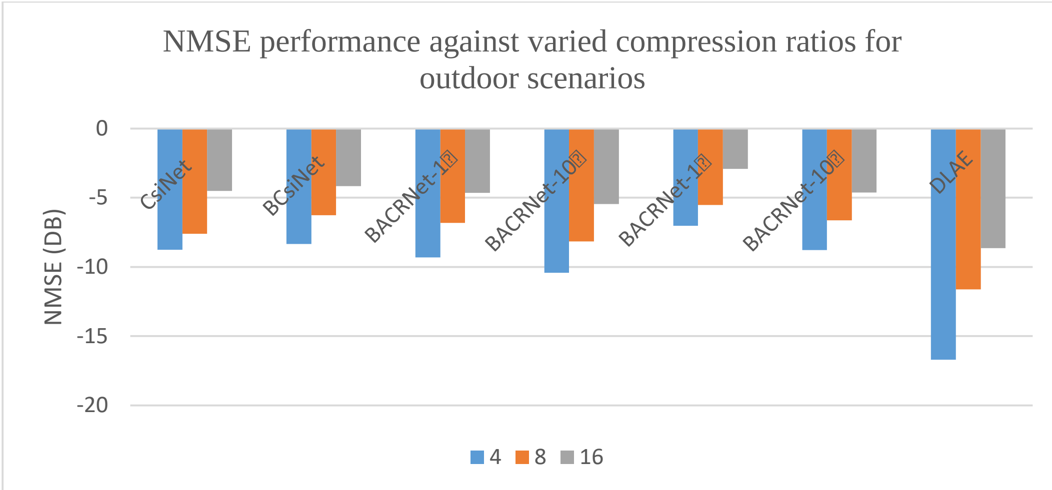

Figure 3: CSI Reconstruction Performance Results Using Proposed DLAE Model and Compared Against Varied CSI Reconstruction Methods Considering Indoor Scenarios

4 Conclusion

Massive Multiple Input Multiple Output (MIMO) systems have been emerged as the main empowering approach to improve spectral efficiency in future wireless communications networks. Therefore, in this article, deep learning-based auto-encoder model is proposed to improve CSI feedback efficiency and reduce channel feedback. The proposed DLAE model enhances spectral efficiency and improves compression capacity. Here, encoder and decoder mechanism are presented to analyse CSI feedback matrices where encoder performs compression of CSI matrices and decoder mechanism is utilized to reconstruct CSI matrices. A comprehensive mathematical modelling of Normalized Complex Coefficients (NCC) supported CSI feedback mechanism is presented to improve channel capacity and reduce channel overhead and computational complexity. Here, NCC supported CSI feedback design is segregated into matrix of CSI feedback which are supported by normalized complex conjugates and energy coefficients. The architecture of NCC supported downlink CSI feedback system is also presented. Here, COST 2100 dataset is utilized to train the network efficiently and evaluate performance of the network. The CSI compression accuracy is improved by 4.27%, 10.34% and 11.69% for compression ratio as 1/4, 1/8 and 1/16 against previous best compression method ACRNet-20× considering indoor cellular environment, respectively. Whereas, CSI compression accuracy is improved by 17.12%, 20.04% and 34.01% for compression ratio as 1/4, 1/8 and 1/16 against previous best compression method ACRNet-20× considering outdoor cellular environment. Performance results verifies that accuracy is much higher using proposed DLAE based CSI reconstruction model.

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