Deep learning-based channel estimation with application to 5G and beyond networks

Parinitha Jayashankar, Shobha Byrappa Nanjundaiah
Department of Electronics and Communication Engineering, S.J.C. Institute of Technology, Chikkaballapur, India

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ABSTRACT

Channel state information (CSI) feedback estimation for a downlink medium in a massive multiple input multiple output (MIMO) system is an essential and critical task to improve channel capacity and performance yield, especially in a frequency division duplex (FDD) multiplexing system. However, spectral efficiency degradation is a massive issue due to high channel feedback overhead. This work proposes a deep learning-based channel estimation (DLCE) model to improve channel reconstruction efficiency and channel overhead reduction accuracy. The proposed deep learning (DL) mechanism consists of encoder and decoder network where encoder network is utilized to compress CSI matrices whereas decoder network is used to decompress obtained CSI matrices. Here, inverse discrete Fourier transform (IDFT) method is utilized to convert CSI matrices of frequency domain into CSI matrices of delay domain. Simulation results are evaluated between uplink and downlink medium in the massive MIMO system considering a co-operation in science and technology (COST) 2,100 model. Here, a significant improvement in correlation and normalized mean square error (NMSE) results is observed. The proposed DLCE model shows superior performance against varied channel estimation techniques in terms of NMSE and correlation efficiency.

Corresponding Author:

Parinitha Jayashankar
Department of Electronics and Communication Engineering, S.J.C. Institute of Technology
Chikkaballapur, Karnataka, India
Email: parinithaj_12@rediffmail.com

1. INTRODUCTION

The telecommunication industry is likely to cultivate endlessly at an emerging rate. This works as a fuel to the modernization and yield of varied industries like agriculture, wireless networks, transportation, finance, consumer electronics, and health care [1]. More specifically, the recent pandemic-coronavirus disease 2019 (COVID-19) outbreak have caused massive disruption and shows how important the telecommunication and information industry is to our society [2]. Thus, a top rated technology, which has gained immense praise from all over the world since last three decades and provided greater yield in many industries is cloud computing technology. This technique has provided immense strength to the information and communication societies. The key features of this technique are high elasticity, on-demand resource access, and large resource storage. Thus, this technique is capable of handling high market demands and expectations without any hassle and management problems. This technique mainly works on principle of pay per use model [3], [4]. However, telecommunication and wireless communication system must handle the ever-rising demands of evolving techniques, devices, and networks to keep up with these trends, which cannot be met by third or fourth generation cellular networks. Therefore, current research mainly focuses on 5 generation (5G) cellular networks or beyond 5G (B5G) networks.

Further, the future 5G or B5G networks can provide data rates up to gigabit-per-second and latency up to few milliseconds with billions of wireless devices remain linked with each other [5]. However, implementation of 5G cellular network requires high bandwidth spectrum as well as lightning speed. Thus, massive multiple input multiple output (MIMO) technique is a top-rated and efficient mechanism to provide immense strength towards future 5G or B5G networks [6], [7]. The main advantages of massive MIMO systems are enhancement of channel capacity and spectral efficiency of a wireless network. The massive MIMO system consists of a base station (BS) and user equipment (UE) in which BS is heavily equipped with hundreds of antennas whereas UE transmit compressed information towards BS for the reconstruction of received information. However, the potential advantages of massive MIMO systems are exploited by the acquisition of channel state information (CSI). However, acquisition of CSI is a critical and channeling task. Further, the performance of massive MIMO system is heavily affected by the CSI acquisition efficiency [8]. Thus, acquisition of CSI in uplink and downlink medium is essential as well as challenging. The CSI acquisition can take place in frequency division duplex (FDD) as well as time division duplex (TDD) domain. Further, in FDD domain, operating frequencies for both uplink and downlink medium are different whereas both uplink and downlink medium remain separated from each other considering varied time-slots. However, CSI acquisition in FDD domain is quite challenging and complex task due to frequency separation of uplink and downlink medium. Thus, downlink medium needs to be predicted at UE and then fed back to the BS via a feedback channel. However, this process can cause high channel overhead. Thus, several researchers have provided their efforts to mitigate channel overhead and improve spectral efficiency of channel estimation.

A CSI compression method is introduced to estimate CSI and compress channel matrices in a massive MIMO systems based on randomized low-rank approximation [9]. This method enhances accuracy precision, reduces computational complexity, and exploits characteristics of channel matrices. According to research by Choi *et al.* [10], a zero-feedback FDD system is adopted to estimate channel matrices in a massive MIMO system. Here, vector spatial signature (VSS) model is also utilized to obtain data of channel measurements. Simulation results are computed in terms of beamforming efficiency and normalized mean square error (NMSE). A deep learning (DL) based mechanism is introduced to estimate channel matrices in a millimetre-wave massive hybrid MIMO system [11]. Here, sparsity of channel matrices is exploited to mitigate channel overhead. Further, a priori and learning model is introduced to study approximated vectors and recover multiple subcarriers. In [12]–[14], a channel reconstruction model is presented for a downlink medium in a massive MIMO system to acquire CSI. Here, reference signals of CSI feedback medium are utilized to back spatial multiplexing to counter power consumption and computational complexity problems. Here, a downlink CSI is reconstructed using sounding reference signals of uplink medium. In [15]–[18], a wideband channel estimation technique is proposed for spatial multiplexing in a massive MIMO system with low-resolution analog-to-digital converters (ADCs). This technique reduces propagation delay and improves inter-symbol interference. Further, a maximum posteriori (MAP) criterion is adopted for channel estimation. In [19], [20], a convolutional neural network architecture is presented to compress channel matrices in a massive MIMO system. Further, a compression sensing based method is utilized to quantize CSI and improves reconstruction accuracy. Here, a CsiNet+ method is adopted to parameter efficiency by 38.0% and 46.7%.

However, implementation of these techniques in practical wireless system is quite challenging due to high interference, massive channel overhead, and lower reconstruction accuracy. Thus, a deep learning-based channel estimation (DLCE) model is proposed in this article in a massive MIMO system. The proposed DLCE technique is utilized to estimate downlink CSI matrices by exploiting correlation between uplink and downlink medium in the massive MIMO system. These channel matrices are obtained from UE feedback and downlink channel matrices are acquired from CSI estimation of uplink medium at source and UE. The proposed DL mechanism consists of encoder and decoder network where encoder network is utilized to compress CSI matrices whereas decoder network is used to decompress obtained CSI matrices. A high quality training is conducted on a large database like co-operation in science and technology (COST) 2,100 dataset using a DL model to improve channel estimation efficiency. Here, efficient CSI feedback code-words are decoded and channel correlation is utilized to improve performance of massive MIMO system. Experimental results are computed using a well-trained DL model in terms of NMSE and channel correlation and compared against several traditional CSI estimation methods.

This article is arranged in following manner. Section 2, discusses about the mathematical representation of channel estimation in a massive MIMO system. In section 3, demonstrates simulation results and their comparative analysis with classical CSI estimation methods and section 4 concludes the paper.

2. MODELLING OF PROPOSED DLCE MODEL

This section discusses about the mathematical representation of DLCE model to estimate channel matrices efficiently and reduce channel overhead in a massive MIMO system. Here, DL based model is adopted to train large dataset and improve channel reconstruction efficiency. Here, multiple antennas are utilized at the BS and channel estimates are acquired at UE and fed back to the BS to reconstruct CSI feedback. Furthermore, downlink CSI medium is estimated using CSI estimation of uplink medium at UE as well as uplink CSI estimation at BS. Figure 1 demonstrates block diagram of downlink CSI feedback mechanism. A detailed mathematical representation of channel overhead reduction and spectral efficiency enhancement in a massive MIMO system is presented in the following section.

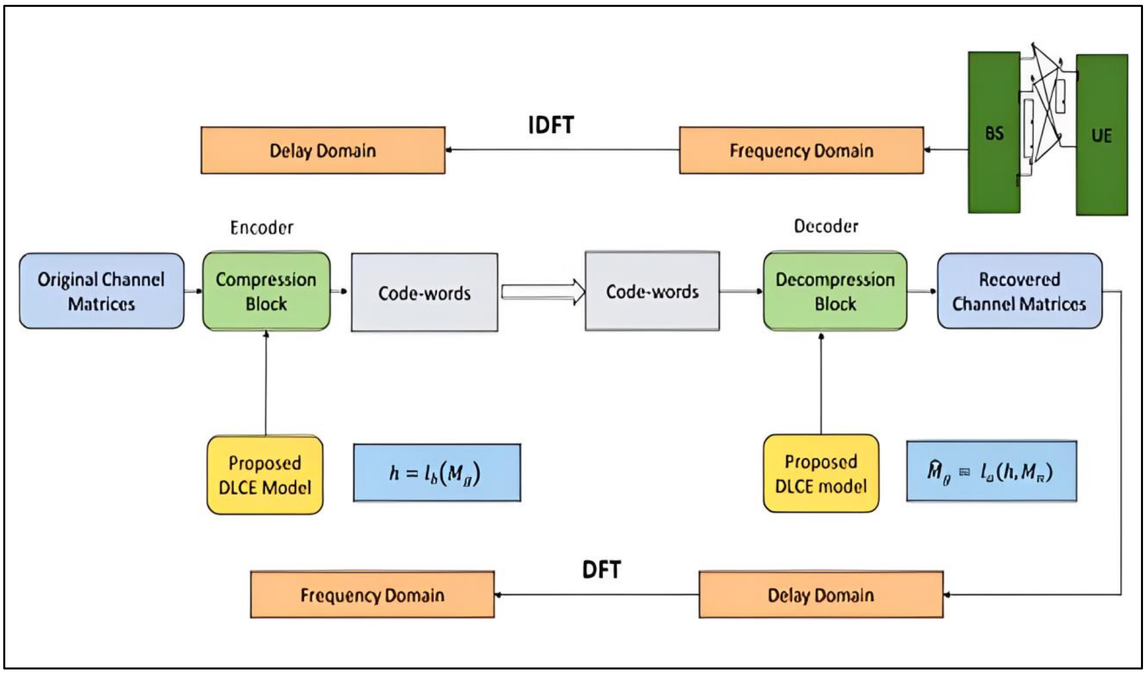

Figure 1. Block diagram of DL based downlink CSI feedback

Here, a study is conducted on a massive MIMO system with a singular cell. Here, the massive MIMO system consists of a BS and UE. Further, a BS consists multiple number of antennas $C_d \gg 1$ and UE is equipped with a singular antenna. Here, orthogonal frequency division multiplexing (OFDM) is adopted in a massive MIMO system considering C_l subcarriers. Then, the received code-words for downlink medium considering $c-$th subcarrier is given by (1).

$$k_g^{(c)} = m_g^{(c)^M} r_S^{(c)} y_g^{(c)} + c_g^{(c)} \tag{1}$$

Where, vector coefficients of a channel considering $c-$th subcarrier are denoted as $m_g^{(c)}$ and proportional to $m_g^{(c)} \in \mathbb{E}^{C_d \times 1}$. Further, broadcasted code-word is given by $y_g^{(c)} \in \mathbb{E}$ and broadcaster beam-former is given by $r_S^{(c)}$ and proportional to $r_S^{(c)} \in \mathbb{E}^{C_d \times 1}$. Moreover, the additional noise is given by $c_g^{(c)} \in \mathbb{E}$ and transpose of conjugates are given by $(\cdot)^M$. Then, the received code-words for uplink medium considering $c-$th subcarrier is given by (2).

$$k_n^{(c)} = r_F^{(c)^M} m_n^{(c)} y_n^{(c)} + r_F^{(c)^M} c_n^{(c)} \tag{2}$$

Where, vector coefficients of a channel considering $c-$th subcarrier are denoted as $m_n^{(c)}$ for an uplink medium and proportional to $m_n^{(c)} \in \mathbb{E}^{C_d \times 1}$. Further, received code-word is given by $y_n^{(c)} \in \mathbb{E}$ and receiver beam-former is given by $r_F^{(c)}$ and proportional to $r_F^{(c)} \in \mathbb{E}^{C_d \times 1}$. Moreover, the additional noise is given by $c_n^{(c)} \in \mathbb{E}$ and transpose of conjugates are given by $(\cdot)^M$ in an uplink medium. Then, the CSI matrices of uplink channel medium in a frequency domain is given by (3).

$$\widetilde{M}_n = \left[m_n^{(1)}, \dots \dots ., m_n^{(C_l)}\right]^M \tag{3}$$

Where, uplink CSI matrices are proportional to $\widetilde{M}_n \in \mathbb{E}^{C_l \times C_d}$. Further, the CSI matrices of downlink channel medium in a frequency domain is given by (4):

$$\widetilde{M}_g = \left[m_g^{(1)}, \dots \dots ., m_g^{(C_l)}\right]^M \tag{4}$$

where, downlink CSI matrices are proportional to $\widetilde{M}_g \in \mathbb{E}^{C_l \times C_d}$. Further, it is considered that the uplink CSI matrices $\widetilde{M}_n$ and downlink CSI matrices $\widetilde{M}_g$ are perfectly obtained by the BS and UE respectively. However, the focus of this study remains on the acquisition of downlink CSI matrices. As mentioned, downlink CSI matrix is proportional to $\widetilde{M}_g \in \mathbb{E}^{C_l \times C_d}$ and due to large size of C_d, the feedback overhead becomes very large in a massive MIMO system. Thus, CSI feedback reduction is handled using a property of channel matrices in which common sparsity is utilized which is present in uplink and downlink medium at the time of CSI estimation in a time-domain. Then, firstly, channel matrix in frequency domain M_l is converted into channel matrix of time domain M_s using an inverse discrete Fourier transform (IDFT) method:

$$M_l L^M = M_s \tag{5}$$

where, L is expressed as a singular DFT matrix which is proportional to $L \in C_d \times C_d$. Whereas, matrix obtained after IDFT process M_s is remain proportional to $C_l \times C_d$. Further, majority elements of matrix M_s are zero or near to zero except the first $\hat{C}_l$ row elements. Thus, zero value elements are discarded so that uplink CSI matrix $\widetilde{M}_n$ and downlink CSI matrix $\widetilde{M}_g$ are expressed as M_n and M_g after IDFT process, respectively. Still, $\hat{C}_l \times C_d$ is considered as large quantity. Thus, CSI matrix M_g is further compressed at UE.

Thus, the proposed massive MIMO system contains encoder and decoder mechanism in which encoder is used to compress CSI matrices and decoder is utilized to reconstruct CSI matrices, respectively. However, the proposed DLCE model estimates downlink CSI feedback matrices with the help of uplink CSI matrices. Assume that the recovered CSI matrix in a downlink medium is denoted as $\widehat{M}_g$. Then, encoder and decoder networks are given by (6) and (7), respectively.

$$h = l_b(M_g) \tag{6}$$

$$\widehat{M}_g = l_a(h, M_n) \tag{7}$$

Thus, the proposed DLCE model shows encoder decoder configuration in which encoder performs compression of CSI matrices and decoder performs reconstruction of obtained CSI matrices and fed them back to the BS from UE. In this way, efficient CSI feedback reconstruction and channel overhead reduction mechanism is presented. Further, CSI matrices of uplink medium acquired at BS and UE are utilized to reconstruct CSI matrices of downlink medium.

Here, the CSI matrices are studied in time domain with the help of correlation coefficients obtained considering uplink and downlink CSI feedback matrices. The obtained CSI matrices are complex in nature in which correlation coefficients are separated into real and imaginary portions. The acquired real and imaginary portions from correlation coefficients considering uplink and downlink medium are uneven and inconsistent. It is examined that channel estimation considering two varied carrier frequency for an FDD system, can contribute to random phase differences between those two carrier frequencies. Thus, it is analysed that from the FDD channel estimation, the magnitude obtained in time domain has higher correlation than the phase obtained in time domain. As a result, correlation of magnitude and phase is evaluated separately by conversion of CSI matrices into polar coordinates. Furthermore, correlation acquired is higher for both uplink channel model and downlink channel model considering magnitude whereas both uplink channel model and downlink channel model, correlation obtained is lower considering phase. Further, real values show better correlation results in contrast to their respective signs considering channel coefficients of both uplink and downlink medium.

Further, the proposed DLCE model evaluates real and imaginary portions of channel correlation coefficients as well as their respective signs which are separately fed back to the BS, unlike classical channel estimation methods. Therefore, this concept is an essential step to mitigate CSI feedback overhead. The main architectural characteristics are utilization of residual blocks, convolutional layer, fully linked layer, and generation of feature maps from obtained high quality features. Here, correlation coefficients of uplink and downlink medium are transformed into real and imaginary portions. As a result, the size of fully linked layers are enhanced and the number of generated feature maps are increase in number. Thus, efficient CSI feedback mechanism is designed by compression of phase and their respective signs considering downlink CSI matrices at the UE. This is due to the low correlation generated by phase. Furthermore, the compressed phase and signs of downlink CSI matrices are fed back to BS from UE and uplink CSI matrices present at the BS, both are decompressed together to achieve downlink CSI channel matrices. In this way, efficient channel reconstruction is achieved as well as channel overhead is mitigated using proposed DLCE model.

3. RESULT AND DISCUSSION

This section discusses about the performance efficiency enhancement using proposed DLCE model in a massive MIMO system. Here, channel estimation is achieved at a rapid rate with the help of DL model, which performs high quality training of channel parameters and coefficients. The proposed DL model reduces utilization of channel parameters to mitigate computation complexity issues. The proposed DLCE model exploits absolute and imaginary portions of correlation coefficients obtained considering uplink and downlink CSI feedback matrices. Besides, correlation coefficients are computed using CSI matrices of uplink and downlink medium. Here, multiple antennas are equipped at BS in a massive MIMO station. Here, efficient CSI feedback code words are compressed at the encoder side and decompressed at the decoder side and channel correlation is utilized to improve performance of massive MIMO system as shown in Figure 1. Here, IDFT method is utilized to convert CSI matrices of frequency domain into CSI matrices of delay domain.

Here, correlation is evaluated between uplink and downlink medium in the massive MIMO system considering a COST 2,100 model [21]. Further, the data present in the COST 2,100 mode is divided into two type of environments such as indoor environment and outdoor environment. Nevertheless, indoor environment is considered in an article in which frequency of uplink medium is set as 5.1 GHz and frequency of downlink medium is fixed at 5.3 GHz. Further, uniform linear array antennas are adopted to improve performance efficiency. In future work, an extension of proposed DLCE model and downlink CSI feedback architecture is presented and experimental results are obtained considering outdoor environment and multi-cell scenarios. The total number of uniform linear array antennas are utilized at BS are $C_d = 32$ and number of subcarriers utilized are $C_l = 1{,}024$. The number of epochs considered for large training are 700 with batch size as 200. The data present in the COST 2,100 dataset is massive and requires efficient training, which is conducted using DL model. The number of parameters utilized in the proposed DLCE model to improve CSI reconstruction accuracy are huge. However, parameter utilization are reduced in comparison with traditional channel estimation methods.

In this section, the obtained experimental results using proposed DLCE model and their comparison with classical channel estimation methods are examined considering COST 2,100 channel model. The data utilized to measure CSI reconstruction accuracy is obtained by efficiency training of COST 2,100 model. The performance accuracy is measured using proposed DLCE model in terms of NMSE and correlation obtained between downlink and uplink CSI matrices against varied compression ratios and the performance efficiency is compared against varied traditional CSI estimation techniques. The obtained simulation results shows efficient results in terms of performance accuracy, NMSE and correlation coefficients and obtained simulation results outperforms traditional CSI feedback estimation techniques.

The simulation results are demonstrated in Table 1 for NMSE against CsiNet [22], [23], CRNet [24], and CsiNetPlus [20] whereas Table 2 shows correlation efficiency against CsiNet and normalized-CsiNet [22]. Further, overall average NMSE is reduced is 9.60% against previous best CSI estimation technique in terms of NMSE. Here, Figure 2 demonstrates graphical representation of performance accuracy using proposed DLCE model against traditional channel estimation methods such as CRNet-Const, CsiNet, DS-NLCSiNet [25] in terms of NMSE results against varied compression ratios. Here, a significant reduction in NMSE results is observed which results in a higher performance accuracy. In contrast to other traditional channel estimation techniques, proposed DLCE model shows lower NMSE results. Here, a significant improvement in NMSE and correlation results is observed. This conclude that the proposed DLCE model efficiently reconstruct downlink CSI feedback matrices as well as reduces channel overhead in contrast to several classical channel estimation techniques.

Table 1. NMSE (dB) using proposed DLCE model for varied compression ratios

CR	CsiNet	CRNet	CsiNetPlus	DLCE
4	-17.36	-26.99	-27.37	**-28.983**
8	-12.70	-16.01	-18.29	**-19.47**
16	-8.65	-11.35	-14.14	**-16.47**

Table 2. Correlation efficiency using proposed DLCE model for varied compression ratios

CR	CsiNet	Norm-CsiNet	DLCE
4	0.99	0.99	0.99
16	0.93	0.94	0.97
32	0.89	0.91	0.96
64	0.87	0.84	0.90

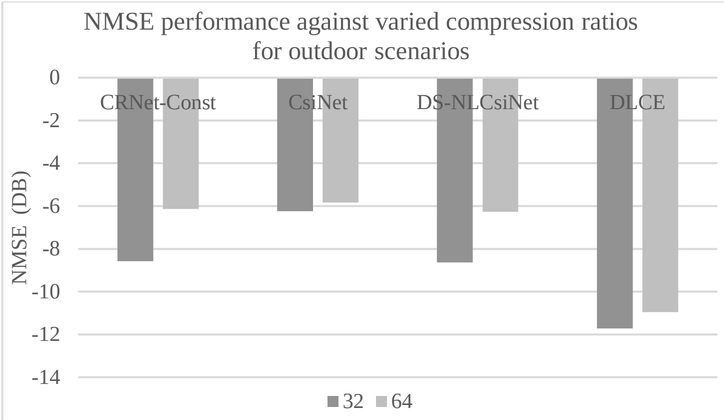

Figure 2. Graphical representation of performance accuracy using proposed DLCE model

4. CONCLUSION

Massive MIMO is quite essential for the practical implementation of future generation high speed networks. Therefore, in this article, a DLCE model is adopted in a massive MIMO system to estimate CSI reconstruction accuracy and mitigate channel overhead reduction. A comprehensive mathematical modelling is presented for the evaluation of correlation coefficients considering uplink and downlink channel medium. The proposed DLCE model exploits absolute and imaginary portions of correlation coefficients obtained considering uplink and downlink CSI feedback matrices. The main architectural characteristics are utilization of residual blocks, convolutional layer, fully linked layer, and generation of feature maps from obtained high quality features. Here, proposed DLCE model utilizes COST 2,100 channel dataset to train CSI matrices. The performance accuracy is measured using proposed DLCE model in terms of NMSE and correlation obtained between downlink and uplink CSI matrices against varied compression ratios. Further, overall average performance accuracy is reduced is 9.60% against previous best CSI estimation technique in terms of NMSE. Thus, the proposed DLCE model outperforms classical channel estimation techniques in terms of NMSE and performance efficiency.

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BIOGRAPHIES OF AUTHORS

Parinitha Jayashankar earned her bachelors of engineering in telecommunication engineering and master's degree in digital communication and networking from Visvesvaraya Technological University (VTU), Belgavi. Currently she is a pursuing her Ph.D. in electronics and communication engineering from Institut Teknologi Sri Jagadguru Chandrashekaranatha, VTU, Belgavi. She is working as an assistant professor with a total experience of 11 years. She has guided over 11 under graduate projects and published 10 papers in various journals. She can be contacted at email: pari.mrj@gmail.com.

Dr. Shobha Byrappa Nanjundaiah is professor and head of the Department of Electronics and Communication Engineering at Institut Teknologi Sri Jagadguru Chandrashekaranatha, Chickbaballpur, Karnataka, Visvesvaraya Technological University, Belgavi. She is having a total experience of 29 years. She is qualified in bachelor and master degrees in electronics from Bangalore University, and Ph.D. from Karpagam University in the field of electronics. She has guided over 60 undergraduate projects, 45 post graduate projects, and guiding 4 Ph.D. students. She has published over 28 papers in various journals and have 6 patents in her name. Her area of interest are bio sensor, image processing, computer vision, embedded system, and IoT. She can be contacted at email: bnshobha67@gmail.com.