International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 08 | Aug 2020 www.irjet.net p-ISSN: 2395-0072

Deep Learning Based Hybrid Precoding For Millimeter Wave Massive MIMO Systems

Sachin K V[1], Gopinath C Y[2]

[1]PG Student, [2]Associate Professor

[1,2]Dept. of Electronics and Communication Engineering, Bangalore Institute of Technology, Karnataka, India

---***---

Abstract - *The spatial diversity offers advantages when Multiple-Input Multiple-Output (MIMO) antenna techniques are considered as compared to traditional point to point MIMO systems. In massive MIMO technology, the Base Station (BS) equipped with large number of antennas serves many users in the same time-frequency network and therefore, it is a promising candidate technology for next generations of wireless systems. Because of the multiplexing gain and the array gain, huge performance can be accomplished with massive antenna arrays, and energy efficiency. Millimeter wave (mmWave) cellular networks will have the data-rates upto gigabits/second. This project introduces a novel neural network architecture, termed as auto-precoder, modeling the hybrid precoding matrices by detecting the mmWave channel with just a few deep-learning based training pilots. A multi-task classification problem is trained in auto-precoder neural network which integrates both channel sensing and beam prediction. The presented method reduces the training overhead substantially comparable with traditional (non-machine learning) approaches. This illustrates a promising solution in mmWave and massive MIMO networks for channel estimation and hybrid precoding architecture challenge.*

Key Words: **Deep Learning, millimeter wave, massive MIMO, channel estimation and hybrid precoding, etc**

1. INTRODUCTION

Hybrid analog/digital systems have drawn tremendous attention over the past couple of years, due to its ability to attain high data rates with energy-efficient devices. Moreover, an accurate estimate of the mmWave channel is usually needed for designing the hybrid precoding matrices. This mmWave channel prediction is a challenging work due to the large number of antennas on transmitters and receivers resulting in high overhead training and the strict hardware limitations on the RF chains. Due to the wide bandwidth available at millimeter wave frequencies, mmWave cellular networks will allow gigabit/second data rates. MmWave communication extends from 30 GHz to 300 GHz and therefore enjoys a much larger bandwidth than modern cellular networks. To realize enough link margin, mmWave devices can use spatial beamforming on both transmitter and the receiver with large antenna arrays. Because of the high cost and power consumption of mixed-signal gigasample devices, mmWave precoding is likely to be split among the analog and digital domains. The vast number of antennas and the inclusion of analog beamforming include the design of channel estimation and precoding algorithms specific to mmWave. Spatial diversity is one of the network diversity systems utilizing more than two antennas to boost efficiency and performance of network connection.

The Need for a Dataset: For the advancement of machine learning work in mmWave and massive MIMO, it is important that researchers have an adequately large dataset can use for (i) assessing their machine learning algorithms performance, (ii) Includes replication in other articles and (iii) Benchmarks are set and the different algorithms are evaluated based on common results

1.1 Objectives of the Project

This project proposes a deep-learning based approach where the channel measurement vectors are mutually optimised and the hybrid beamforming vectors are designed with minimal overhead training to achieve near optimum data rates. In particular, neural network architecture called as auto precoder is developed to attain two key goals: (i) It improves the compressive channel sensing vectors depending on the surrounding area to target its sensing capacity in an unsupervised manner in the desirable spatial directions. (ii) The hybrid beamforming vectors are directly predicted from received sensing vector.

Attaining these two goals resulting in a successful strategy for channel precoding/sensing architecture that could project near-optimal beam-forming hybrid vectors despite requiring minimal overhead training.

1.2 Motivation

Even though there are optimisation-based methods which approximate the precoders directly, they tend to be huge computational local-minimum complexity and issues related to random seperation. Also, hybrid precoders are designed for the effective MIMO multiple user situation, even though extremely realistic Importance, was not regarded in comparison to deep learning. Therefore, powered by the advantages of deep learning such as its low computational complexities, a system is created which can manage the hybrid precoding model when multi-user MIMO transmission is disrupted in the mmWave area feedback on channels is available.

2. SYSTEM AND CHANNEL MODELS

The fully-connected hybrid architecture depicted in figure 1, in which a transmitter using N_t antennas and some N_t^{RF} RF chains interacts via receiver using N_r antennas and N_r^{RF} RF chains using N_s streams.

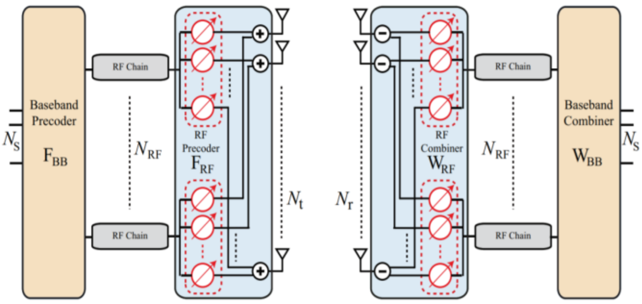


Figure 1: A system architecture for hybrid analog/digital transceiver

Considering the complete hybrid architecture depicted in figure 1, the transmitter uses N_t antennas and N_t^{RF} RF chains interacts to a receiver using N_r antennas and N_r^{RF} RF chains through N_S streams. Transmitted signal is precoded using transmitter with the $N_t^{RF}\times N_S$ baseband precoder and the $N_t\times N_t^{RF}$ RF precoder whereas the receiver integrates the obtained signal with the $N_r\times N_r^{RF}$ RF combiner and its baseband combiner $Nr^R\times NS$. Normalization of the baseband precoder to satisfy $||F_{RF}F_{BB}||^2{}_F = N_S$ enforces the total power limit. Graphical channel layout of L-paths is adopted for the channels between transmitter and receiver antennas. The $N_r\times N_t$ channel matrix H in this system is written as,

$$H = \sum_{l=1}^{L} \alpha_l \, a_r(\emptyset_{r,l}, \theta_{r,l}) \, a_t^H(\emptyset_{t,l}, \theta_{t,l}) \qquad (1)$$

The achievable rate can be defined for hybrid precoders as,

$$R = log_2 \,|\, I + R_n^{-1} \, W^H HFF^H H^H W \,| \qquad (2)$$

Where, $F = F_{RF}F_{BB}$ and $W = W_{RF}W_{BB}$. The matrix $R_n = (1/SNR)*W^HW$ depicts the equation of noise covariance in which $SNR = P_T/(N_S\sigma^2{}_n)$ and with P_T denotes the total transmitting power and $\sigma^2{}_n$ denotes noise power. RF beamforming vectors are chosen by the predetermined quantified codebooks. After defining the channel, the design problem of the hybrid precoder can be described as,

$$\{F_{BB}^*, F_{RF}^*, W_{BB}^*, W_{RF}^*\} = \text{argmax} \log_2 |I + R_n^{-1} W^H HFF^H H^H W| \qquad (3)$$

$$\text{s.t} \quad F = F_{BB} F_{RF} \qquad (4)$$

$$W = W_{BB} W_{RF} \qquad (5)$$

$$[F_{RF}]_{:,} n_t \in \mathcal{F}, \forall n_t \qquad (6)$$

$$[W_{RF}]_{:,} n_r \in \mathcal{W} \forall n_r \qquad (7)$$

$$||F_{RF} F_{BB}||_F^2 = N_S \qquad (8)$$

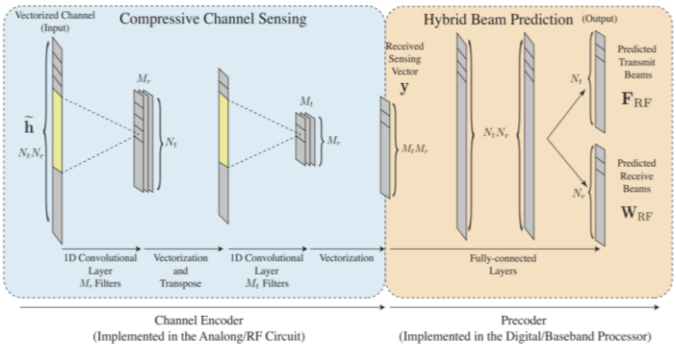
The optimal baseband precoders F_{RF} and W_{RF} are defined for chosen RF precoders when the RF beam-forming codebooks comprise of orthogonal vectors as,

$$\{F_{RF}^*, W_{RF}^*\} = \underset{\substack{[F_{RF}]_{:,n_t} \in \mathcal{F}, \forall n_t \\ [W_{RF}]_{:,n_r} \in \mathcal{W} \forall n_r}}{\text{argmax}} \log_2 |\, I + SNR W_{RF}^H HF_{RF} \times (F_{RF}^H F_{RF})^{-1} F_{RF}^H H^H W_{RF}| \qquad (9)$$

The problem formulation in (9) states that hybrid precoders could be identified by an extensive study over RF beam-forming vectors. The problem moreover, is that channel is usually uncertain and its clear estimate involves very high overhead training in the mmWave model. To overcome this problem, the goal is to formulate a method that specifically defines the hybrid architecture precoding RF vectors that optimize (or approach) the optimally attainable rate despite allowing low-channel overhead training.

3. NEURAL NETWORK DESIGN FOR HYBRID PRECODING

In this project a neural network architecture is proposed called an auto-precoder and the channels are sensed by deep learning method where the hybrid beam-forming vectors are designed directly through compressed measurements.



Equation 4.2

Figure 2: The neural network proposed for auto-precoder.

The figure 2 illustrates the block diagram of neural network of auto-precoder. It consists of two sections, one of which is a channel encoder and other being a precoder. The channel encoder uses the vector representation channel matrix as an input and send it across two 1D-convolution layers representing Kronecker (⊗) product operation of transmitting and receiving measuring matrices.

The Kronecker product, also referred to as ⊗, is a two-matrices operation of arbitrary size which results in a block matrix. This is a representation of the outer product through vectors to matrices and provides the representation of the tensor product to the traditional choice of the basis. The Kronecker product must never be mistaken with regular multiplication of the matrix, which is a completely distinct operation. The result of the channel encoder will be fed into the precoder. The precoder comprised of two sets of fully connected layers and two output predicted beams for predicting the index of N_t^{RF} RF beam-forming vectors and the N_r^{RF} RF combining vectors of the hybrid architecture.

3.1 Millimeter Wave Auto-Precoder

The auto-precoder network comprised of two divisions: (i) Firstly channel encoder studies how compressive sensing vectors can be refined to target sensing capacity on the most successful approaches. (ii) The precoder that knows how RF beam-forming vectors of hybrid architecture can be predicted from output of channel encoder. The auto-precoder network can be trained and utilized as follows to attain the objectives.

i. Auto Precoding Training: The auto-precoder gets trained in sequential pattern during the training process. More precisely, a mmWave channel dataset and the associated RF beamforming matrices are developed and the auto-precoder is predicted by training hybrid RF precoding vector indices. The RF beamforming matrices was built which used the near optimum Gram Schmidt hybrid beamforming algorithm. The channel encoder depicted in figure 2 knows how to refine its compressed sensing vectors by training the auto-precoder framework.

ii. Auto-Precoder Prediction: After the training of auto-precoder network, this is seperated in two sections within the prediction stage. Firstly the channel encoder is applied explicitly in analog circuits. Most precisely, both transmitter and the receiver would use weights of two convolutionary layers of channel encoder as the weights of analog/RF measurement matrix. The unique architecture of channel encoder as stated in section 3.2 is allowed. Detecting the uncertain mmWave channel matrix must use these deep-learning optimized measuring matrices. Secondly the channel measurement output which is the receiver sensing vector would be processed into the precoder and further used to estimate the indices of RF beamforming vectors.

3.2 Millimeter Wave Compressive Channel Sensing

Enhancing the sparsity of the millimeter wave signal, [2] suggested to exploit compressive sensing devices to detect and recreate the millimeter wave hybrid transmitters and receivers. A neural network architecture is designed which integrates the compressive sensing paradigm and enables the network architecture to refine the measuring vectors depending on the ambient environment. Considering the channel models, let P and Q represent the channel measurement matrices ($N_t \times M_t$ and $N_r \times M_r$) implemented by both the transceiver for channel H, with the number of transceiver measurements defined by M_t and M_r. If the pilot symbols are 1, it is possible to write the received measuring matrix Y as,

$$Y = \sqrt{P_T} Q^H HP + Q^H V \tag{10}$$

where $[V]_{m,n} \sim N_C(0, \sigma_n^2)$ is the noise of the receiving measurement. Therefore, when the measuring matrix y is vectorised, the obtained equation is,

$$y = \sqrt{P_T}\left(P^T \otimes Q^H\right)h + v_q \tag{11}$$

where y = vec (Y), v = vec ($Q^H V$) and h = vec (H). In traditional methods to signal processing, transceivers do not usually make use of earlier research and thus have no awareness of the most suitable spatial directions of channel measurements. Consequently, traditional compressive channel sensing methods usually follow random vector calculation.

Channel Encoder Network Architecture: The implementation of channel sensitivity as seen in (11), the product of vector channel h as well as the two measurement matrices are being replicated by inserting the channel into the network composed of two successive convolutionary layers, as seen in figure 2. In the design M_r filters are employed by first convolutionary layer. Each kernel will have a size of N_r and phase of N_r, which describes one receive vector of measurement. More precisely, each kernel's weights explicitly reflect the inputs from receiver calculation vector. The first convolutionary layer result has feature maps of M_r. The matrix of such characteristic maps is vectorized and inserted further into second convolutionary row. Relative to first layer, the second convolutionary layer is composed of Mt kernels that follow the P transmission computation matrix. This is worth noting here that because the measuring weights of the transceiver are typically complicated, the multi-evaluated neural network model of the convolution layers are followed.

The training of autoprecoder as explained in section 3.1 trains the channel encoder to refine its transreceive compressive channel calculation matrices in an implicit fashion. Such optimization instinctively modifies the measurement matrices both to vicinity area and device application, thus concentrates the sensor capacity for appealing physical paths. Once the training of model is over, the channel encoder kernel will then be directly used by the transceiver as the measurement matrices for sensing the undiscovered channels. To determine the RF beamforming vectors, the output of the channel measurement must be fed into precoder of figure 2 and it is second portion of auto precoder network.

3.3 Hybrid Beam Prediction

Incorporating deep learning models from the obtained channel estimation vector y to know the direct mapping feature from its obtained vector y as well as the beamforming vector. The proposed methodology concentrates on estimating the RF beamforming integrating F_{RF} and W_{RF} vectors for convenience. After the design of RF beamforming vectors, the low-dimensioned efficient

$W_{RF}^{H}HF_{RF}$ channel can be conveniently measured and used to create the precoders and combiners for the beseband. Furthermore, as the RF beam-forming vectors are chosen by its quantized codebooks, formulating issue of determining RF beamforming vector index as a multi-label categoriztion issue. Further the network architecture adopted for hybrid beam prediction is explained in brief.

Network Architecture of Precoder: The proposed neural network architecture of autoprecoder illustrated in figure 2 estimates the indices of the RF beam-forming vectors from receiver measuring vector y. This system comprises of two sets of fully connected layers as well as two output layers where it is inputed by the 'channel encoder' network output specified in section 3.2. The two sets of fully connected layers comprises of Relu activation and batch normalization as the first set and Sigmiod and batch normalization as the second set. The system comprises of two output layers where first layer predicts the indices of beamforming vectors of transmission while in the second layer, the indices of combining vectors of the reception are predicted. The auto-precoder framework is equipped in a Multi Task Learning (MTL) way, treating RF precoding configuration and integrating the hybrid architecture matrices as two linked functions. Therefore, the network is then trained to combine these two functions simultaneously, and thus allows for dependency among precoding and combining matrices.

3.4 Training and Predicting the Deep Learning Architecture

The autoprecoder network as shown in figure 2 is being trained as a learning based problem being part of deep-learning category as briefed in section 3.1 and 3.3. Generally neural network is trained depending on channel matrix dataset and associated hybrid model RF beam-forming vector. The RF precoding matrices are determined by using Gram-Schimdt hybrid precoding (GS-HP) algorithm. The goal is to build a reduced-complexity algorithm that performs similarly (or quite near) to the Direct Greedy Hybrid Precoding (DG-HP) algorithm. The labeling for the beamforming vectors of transmitter and combining vectors of reciever are defined as N_t^{RF} hot vectors, for those at the positions that match the indices of intended RF beam-forming codewords (from codebook F).

For loss function, binary cross entropy is used to distinguish multi-label, which correlates from each task. The overall loss factor is the mean of two tasks of binary cross-entropies, as they are similarly necessary for whole purpose of hybrid precoding or combing architecture. Sample-wise precision of estimated indices is calculated to determine the efficiency of the prediction. The precision of the sample i is then defined as,

$$a_i = \frac{|\, y_{true}^{(i)} \cap y_{pred}^{(i)} \,|}{|\, y_{true}^{(i)} \,|} \tag{12}$$

where ∩ represents two sets intersection. Therefore, the sample-wise accuracy is defined as,

$$a = \frac{\sum_{i=1}^{N} a_i}{N_{samples}} \tag{13}$$

Here $N_{samples}$ represents sample number. The two commonly accepted output metrics are reduced to (12) because the amount of label for each channels would be a defined number for real labels and estimated labels.

The neural network architecture shown in figure 2 meets two specific goals in this training period: (i) It enhances the transmission/reception measuring vectors in an un-supervised way to guide sensitivity power in its most succesful ways. (ii) Understands predicting hybrid architecture RF beamforming/combining vectors directly by channel measuring vectors via the precoder network.

3.5 Training of datasets

The generated datasets use the generic DeepMIMO datasets that are publicly available. The parameters are listed in table 1.

Table 1: Parameters adopted for Deepmimo dataset

Parameters for DeepMIMO Dataset	Values
Activated Base Stations	4
Activated mobile users	From R1200 to R1500 row
Number of BS Antennas	Mx = 01, My = 64, Mz = 01
Number of User Antennas	Mx = 01, My = 64, Mz = 01
Antenna spacing (wavelength)	0:5
System bandwidth (GHz)	0:5
OFDM subcarriers	1024
OFDM sampling factor	01
OFDM limit	01
Number of paths	03

The auto-precoder neural network is trained using constructed dataset. The system is designed with Theano backend using Keras library. Adam optimizer is used with 0.5 momentum, 512 as batchsize and 0.005 as learning rate.

Initially four base-stations are considered in the exterior scenario which communicates to the active users from row number R1200 to R1500 through uplink configuration. Both mobile users and BS are employed with 64 antennas each and three RF chains. Initially the channel matrix is constructed with the help of DeepMIMO dataset generator. However the channel matrix is summed with random noise and depending on 0.5GHz bandwidth and 5dB receive noise figure, the noise power is being calculated. The near-optimum Gram Schmidt hybrid precoding algorithm is used to build target RF precoding matrices in the noisy channel pair and respective RF precoding codebook indices are referred as one data-point in dataset.

4. RESULTS

To determine the hybrid precoding system centered on deep learning, achievable rate is measured using the expected precoding/combining and comparing indices to its optimum rate. Precisely, the presented auto-precoder neural network architecture in section 3 for predicting the appropriate set of RF precoding matrix for hybrid architecture is used for defined noisy channel calculation. Then, attainable rate is calculated as described in (2) by implementing the precoding/combining design of the baseband. This performance will be contrasted with the optimum rate obtained when computing the precoding/combining matrices as described in section 3.5 with complete knowledge of the channels.

The results listed below is the achievable rate calculated by the use of estimated precoding indices and compared with optimum indices. The figure 3 represents the simulated model that can attain desirable throughput while decreasing the pilot training, that is only a limited amount of channel measurements Mt, Mr.

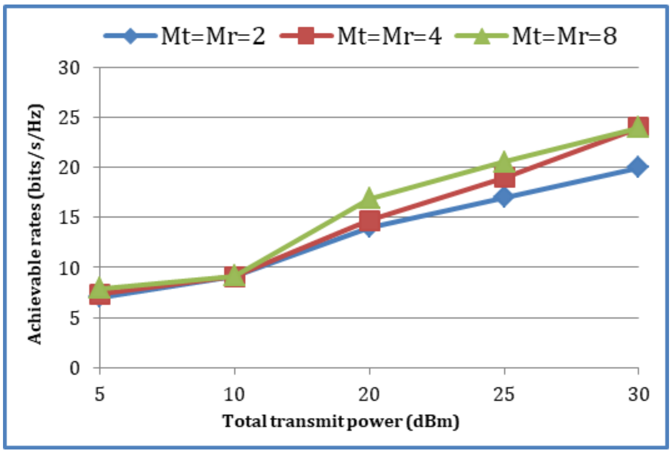


Figure 3: The achievable rates of the proposed method for various values of total transmit power P_T.

The figure 3 describes the achievable rate of the presented hybrid precoding based on deep-learning approach with its average value versus values of total Transmitting Power (PT). Further the graph for achievable rate of the proposed methodology for channel measurements $M_t = M_r = 2, 4, 8$ channel measurements is plotted. It represents the efficiency of the proposed system at reasonable values of PT and also represents the decrease in training overhead needed relative to conventional methods.

Besides the attainable rate (key Purpose of the project), the efficiency of the presented deep learning architecture is also evaluated by utilizing sample-wise precision described in section 3.4. The capability of deep Learning architecture to predict the appropriate collection of RF beamforming/ combining matrices is evaluated by sample wise precision. Considering figure 3, similar models of system and channel are adopted in figure 4 and describe the sample precision of transmission beams and receiver beams of various parameters of PT.

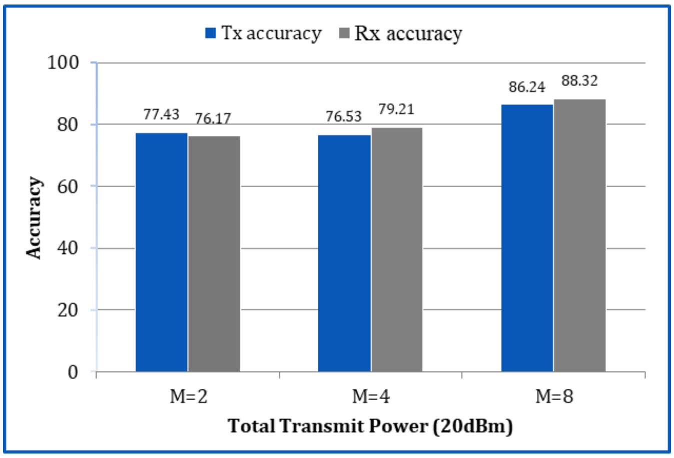


Figure 4: Sample wise accuracy

The figure 4 represents evaluation of the results by using sample-wise precision of the proposed neural network. This analyzes the deep learning model's ability to predict the appropriate set of RF beamforming vectors for hybrid architecture.

5. Conclusion

This project presented deep-learning model in mmWave massive MIMO systems for sensing joint channel and hybrid precoding architecture to improve the attainable rate of the model by reducing training pilots. First, the channel encoder studies considering the neural architecture to improve the channel sensation vectors to concentrate the sensing capacity upon its successful approaches. Further, the precoder starts predicting the the hybrid architecture RF beamforming/combining vectors directly from obtained sensing vector. Analytical results revealed that the proposed approach based on deep-learning would accurately predict hybrid beamforming vectors that attain desirable data-rate needing few training pilots relative to extensive analysis and standard compression sensing alternatives.

REFERENCES

[1] Noha Hassan and Xavier Fernando, “Massive MIMO Wireless Networks: An Overview”, WWW.mdpi.com/journal/electronics, 2017.

[2] Ahmed Alkhateeb, Omar El Ayach, Geert Leus, and Robert W. Heath Jr, “Channel Estimation and Hybrid Precoding for Millimeter Wave Cellular Systems”, IEEE Journal of Selected Topics in Signal Processing, 2013.

[3] Ran Zhang, Weixia Zou, Ye Wang, and Mingyang Cui, "Hybrid Precoder and Combiner Design for Single-User mmWave MIMO Systems", IEEE Access, January 25, 2019.

[4] Ahmed Alkhateeb, "DeepMIMO: A Generic Deep Learning Dataset for Millimeter Wave and Massive MIMO Applications", arXiv:1902.06435v1 [cs.IT], 18 Feb 2019.

[5] Anil Kurt, Gokhan M. Guvensen, "An Efficient Hybrid Beamforming and Channel Acquisition for Wideband mm-Wave Massive MIMO Channels", IEEE International Conference on Communications (ICC), 2019.

[6] Ahmet M. Elbir and Anastasios Papazafeiropoulos, "Hybrid Precoding for Multi-User Millimeter Wave Massive MIMO Systems: A Deep Learning Approach", IEEE Transactions on Vehicular Technology, 2019.

[7] Salem Alemaishat, Omar A. Saraereh, Imran Khan, Sophene H. Affes, Xingwang Li and Jeong Woo Lee, "An Efficient Precoding Scheme for Millimeter-Wave Massive MIMO Systems", WWW.mdpi.com/journal/electronics, 2019.

[8] Hongji Huang, Yiwei Song, Jie Yang, Guan Gui, and Fumiyuki Adachi, "Deep-Learning-based Millimeter-Wave Massive MIMO for Hybrid Precoding", IEEE Transactions on Vehicular Technology, 2018.

[9] Xianru Liu, Xueming Li, Shu Cao, Qingyong Deng, Rong Ran, Kien Nguyen and Tingrui Pei, "Hybrid Precoding for Massive mmWave MIMO Systems", IEEE Access, Volume:7, 2019.

[10] Chao-Kai Wen, Wan-Ting Shih, and Shi Jin, "Deep Learning for Massive MIMO CSI Feedback", IEEE Wireless Communications Letters, Volume:7, Issue:5, 2018.

[11] Duy H. N. Nguyen, Long B. Le, Tho Le-Ngoc, and Robert W. Heath Jr, "Hybrid MMSE Precoding and Combining Designs for mmWave Multiuser Systems", IEEE Access, Volume:5, 2018.

[12] Shiwen He, Jiaheng Wang, Yongming Huang, Bjorn Ottersten, and Wei Hong, "Codebook Based Hybrid Precoding for Millimeter Wave Multiuser Systems", IEEE Transactions on Signal Processing, Volume: 65, Issue: 20, 2017.