Deep Learning Based Analog Beamforming Design for Millimetre Wave Massive MIMO System

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Deep Learning Based Analog Beamforming Design for Millimetre Wave Massive MIMO System

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Abstract: Analog beamforming (ABF) architectures for both large-scale antennas at base station (BS) and small-scale antennas at user side in millimetre wave (mmWave) channel are constructed and investigated in this paper with the aid of deep learning (DL) techniques. Transmit and receive beamformers are selected through offline training of ABF network that accepts input as channel. The joint optimization of both beamformers based on DL for maximization of spectral efficiency (SE) for massive multiple input multiple output (M-MIMO) system has been employed. This design procedure is carried out under imperfect channel state information (CSI) conditions and the proposed design of precoders and combiners shows robustness to imperfect CSI. The simulation results verify the superiority in terms of SE of deep neutral network (DNN) enabled beamforming (BF) design of mmWave massive MIMO system compared with the conventional BF algorithms while lessening the computational complexity.

Keywords: Deep learning; millimeter wave; beamforming design; large-scale antenna arrays; analog beamformers; massive multiple input multiple output.

1. Introduction

Beamforming is a technique to steer beams of multiple antennas at base station (BS) to desired user equipment (UE), that helps to make effective implementation of massive multiple input multiple output (M-MIMO) systems. The problem of high energy consumption by large number of radio frequency (RF) chains becomes significant in millimeter wave (mmWave) communication and so antenna arrays at BS requires beamforming for the directional transmission of signal. The architectures of beamforming techniques are categorized into three forms namely, digital, analog and hybrid beamforming

A single RF chain is dedicated to each antenna known as digital beamforming and it is feasible to implement in conventional massive multiple input multiple output (MIMO) systems but impractical to implement in M-MIMO systems. The large number of antennas in M-MIMO results in equally large number of RF chains. The RF chains are costlier and have high energy consumption, and becomes more critical in mmWave M-MIMO systems. The remedy of this problem is to implement hybrid (analog/digital) beamforming. Hybrid analog and digital beamforming (HBF) architecture has been deemed as a core candidate for large-scale antenna arrays multiple input multiple output (MIMO) systems for its uniqueness in reducing hardware complexity and chasing the performance of fully-digital beamforming. These benefits are more profound especially in millimeter wave (mmWave) communication due to its sparse multipath channel structure. This architecture is realized by connecting a large number of antennas using a network of digitally controlled phase shifters known as analog beamformer to a small number of radio frequency (RF) chains known as digital beamformer.

A lot of researchers inspired from beamforming the antennas has been paved many ways to address the steering beams at desired direction in the past two decades. Sayeed et al. proposed virtual representation of channel w.r.t. fixed spatial basis functions defined by fixed virtual angles [1]. Several research groups [2, 3, 4, 5] adopted the hybrid selection/MIMO approach (antenna selection) to reduce number of RF chains in MIMO. Sayeed and Raghavan found the impact of reconfigurable antenna arrays on maximizing capacity in sparse multipath environments [6]. Authors also proposed a model for sparse multipath channel. Venkateswaran and Veen used analog beamforming via phase shifting network [7]. Sayeed and Behdad also employed a novel antenna array architecture called discrete lens antenna array [8], also known as continuous aperture phased (CAP) MIMO architecture based on hybrid analog-digital architecture. The researchers also claimed that this architecture was ideal for mmWave communication. Alkhateeb et al. developed hybrid analog-digital precoding at BS and analog combining at multiple receive antennas for downlink M-MIMO mmWave system [9].

The conventional hybrid architecture for M-MIMO were based on phase shifters. Méndez-Rial et al. proposed new hybrid architecture based on switching network [10] which reduced complexity and improved EE of the system. Zeng et al. implemented practical setup of mmWave M-MIMO system using lens antenna array [11], and evaluated error response of lens antenna array and throughput gain. Gao et al. compared low RF complexity beamforming technologies, i.e., phased array-based hybrid precoding (PAHP) with lens array-based hybrid precoding (LAHP) [12]. PAHP provided higher SE than LAHP, whereas LAHP achieved higher EE than PAHP.

Meanwhile, there is a need to be optimized by various performance metrics of the precoder (digital and analog) and combiner (digital and analog) to fully utilize the available network resources. Some important indicators are minimization of mean square error (MSE) and maximization of spectral efficiency (SE). But, the constant modulus constraint on analog beamformers suffers difficulty to cope along with digital beamformers, turning it out to be the hardest challenge in HBF optimization of system design.

Various model-based design approaches are explored by distinct research groups to combat the constant modulus constraint on analog beamformers. Ayach et al. formulated HBF precoding as spatially sparse reconstruction via orthogonal matching pursuit (OMP) algorithm and HBF combining using minimization of MSE [13]. The adaptive channel estimation scheme for hybrid precoding has been proposed by Alkhateeb et al. [14]. For bringing low complexity and high SE together, manifold alternating minimization scheme for designing hybrid precoder is proposed by Yu et al. [15]. The maximization of SE in a single user MIMO and multi user multiple input single output (MISO) using fully-connected and partially-connected hybrid architectures are carried out by Sohrabi and Yu [16]. The precoding design reliant on minimum MSE (MMSE) criterion as in [17] and [18] also reaches performance comparable to maximization of SE. Lin et al. investigated HBF design for broadband mmWave transmissions on MMSE criterion [19].

Furthermore, these BF techniques proposed in the previous works require loads of time-consuming serial iterations with high computational complexity proportional to the number of phase shifters in use [20]. However, as the development of data-based deep learning (DL) methods are at peak and are also able to uphold the effective solutions of the conventional challenging problems [17], so it is highly desirable to set forth DL techniques for HBF optimization. Alongside DL after offline training shows minimal complexity at online deployment stage and also emerges an excellent tool to handle the characteristics of large number of training samples of complex wireless channels. In HBF aspect, DL has been employed by various research groups by replacing the non-convex BF optimization in conventional HBF with designed end to end deep learning neural networks (DNN). Some of the pioneering works in DL beamforming design are mentioned below:

A DL mmWave massive MIMO has been developed for hybrid precoding by Huang et al. [21]. Alkhateeb et al. employed DL for coordinated beam training in [22] to enhance the reliability of highly mobile mmWave systems. In addition, a DNN based on few constraints for reconstructing output as input is designed by Tao et al. [23] for mmWave HBF massive MIMO system. The perfect channel state information (CSI) is assumed in most of the works. But, Li and Alkhateeb considered imperfect CSI by applying DL to sense mmWave channel and design hybrid precoding jointly [24]. It can be observed that the works dedicated to DL frame work of HBF achieve better performance than conventional HBF [25]. Further, beamforming scheduling model for massive MIMO system is proposed using reinforcement learning by Zang and Sun [26]. Lin and Zhu offered a new design approach in place of end-to-end DL communication link [27], which returns the optimized analog beamformers restricting to the constraints. For ease of presentation, the analog beamforming (ABF) design aided by DL was considered for large scale antenna array at transmitter side i.e., multiple input single output (MISO) system having single RF chain.

In this paper, the integration of DL with ABF in mmWave massive MIMO single user system has been investigated. Inspired from DL aided ABF design at precoding stage by Lin and Zhu [27], the joint optimization of two analog beamformers at precoding and combining stages by considering the constraint of SE maximization has been proposed in this work. The superior learning capability of DL aids the whole system into a black box to analyze the characteristics of ABF system. This work further considers imperfect CSI explicitly. Instead of implementation of traditional neural networks and training of whole communication system, ABF DNN system is developed based on work by Lin and Zhu [27], which reliably yields the optimized analog beamformers based on the channel input. Because of definite architecture of analog beamformers which employ analog phase shifters, the traditional neural networks cannot be implemented. This paper seeks to propose a general

ABF design which can handle analog beamformers jointly at transmitter as well as receiver end rather than analog BF at one end. This model can be used for online deployment for any diverse channel conditions.

The remainder of this paper is organized as follows: Section 2 introduces various forms of beamforming of M-MIMO system. Section 3 presents mmWave massive MIMO system model with analog beamformer optimization problem formulation for a single user. Section 4 provides DNN framework of ABF design along with its algorithm. Simulation results for the performance of proposed framework are provided in Section 5 and concluding remarks with some future research directions are provided in Section 6.

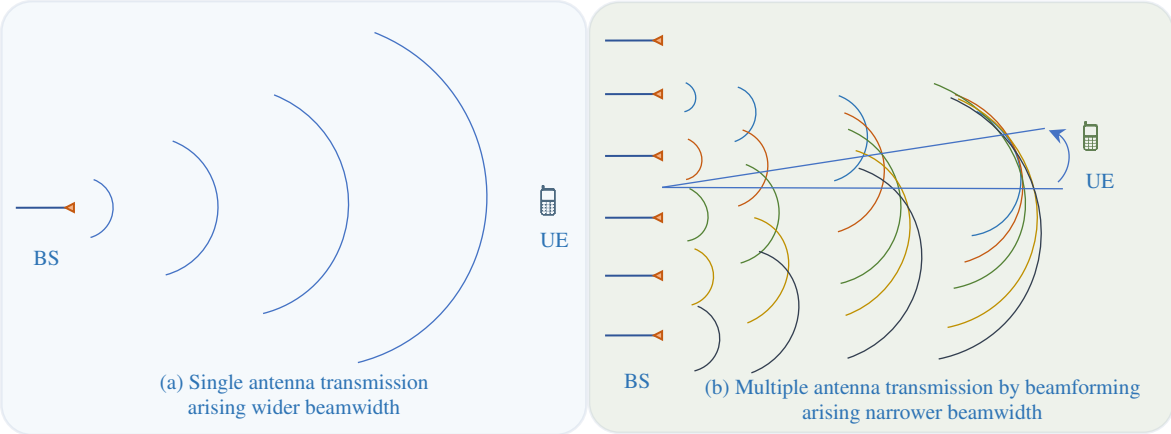

Figure 1 Creating directional waves by varying phase angle and amplitude of each antenna

2. Beamforming

In single antenna system, there is a lack in controllability of beam direction as shown in Figure 1 (a). The directional transmission by antenna arrays at BS necessitates beamforming. Beamforming is a spatial filtering scheme to transmit or receive data signals from all the antennas by manipulating phase and amplitude in order to direct the data signals in desired directions constructively or destructively as shown in Figure 1 (b). The architecture of beamforming techniques is classified into three categories as digital, analog and hybrid beamforming [2, 3, 4, 5, 28, 29].

2.1. Digital beamforming

In digital beamforming technique, each antenna has its own dedicated RF chain. It provides high degrees of freedom, as it permits manipulation of signal's phase and amplitude on every antenna. But to have a dedicated RF chain for every antenna is a hardware constraint especially in mmWave communication. Therefore, implementation of fully digital beamforming in mmWave is expensive and complex. [30, 28, 31, 29].

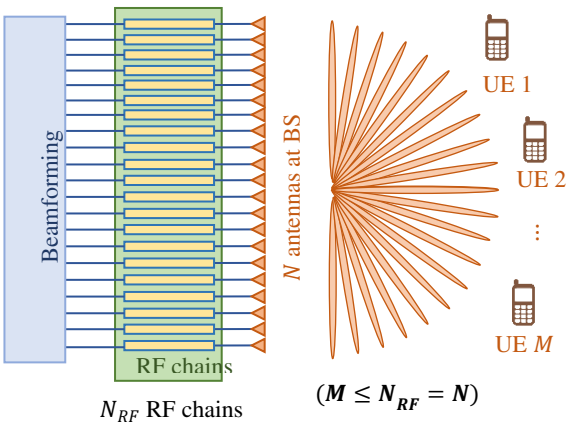

Figure 2 System model of conventional M-MIMO (fully digital M-MIMO)

In conventional M-MIMO system, digital beamforming is employed where each antenna element is equipped with one RF chain, as illustrated in Figure 2. The required number of RF chains N_{RF} is equal to the number of antenna elements N, serving M UEs such that $(M \leq N_{RF} = N)$ [32].

2.2. Analog beamforming

Instead of digital beamforming, a simpler and inexpensive approach is analog beamforming, used in implementation of mmWave M-MIMO systems. It is realized by connecting antennas through a network of digitally controlled phase shifters to a single RF chain, using small number of quantized phase shifts as shown in Figure 3. The phase shifters are inexpensive and consume less power as compared to RF chains. The key drawback of this technique is that it provides less degrees of freedom, due to a single beamformer [30, 28, 29]. The fine tuning of beams and steering nulls for attending large antennas are challenges in analog beamforming M-MIMO.

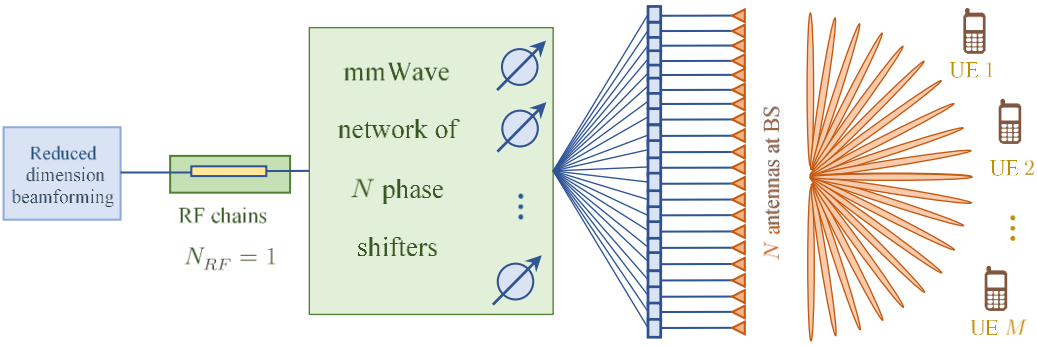

Figure 3 System model of analog beamforming M-MIMO

2.3. Hybrid beamforming

To cater the benefits of both techniques together, combination of digital and analog known as hybrid beamforming is implemented in mmWave M-MIMO system. The number of RF chains gets reduced depending upon number of UEs. It is done in between a small number of RF chains and a large number of antennas by using a network of digitally controlled phase shifters as shown in Figure 4. Instead of phase shifting networks, switching networks can also be used [8, 7, 10, 33, 12].

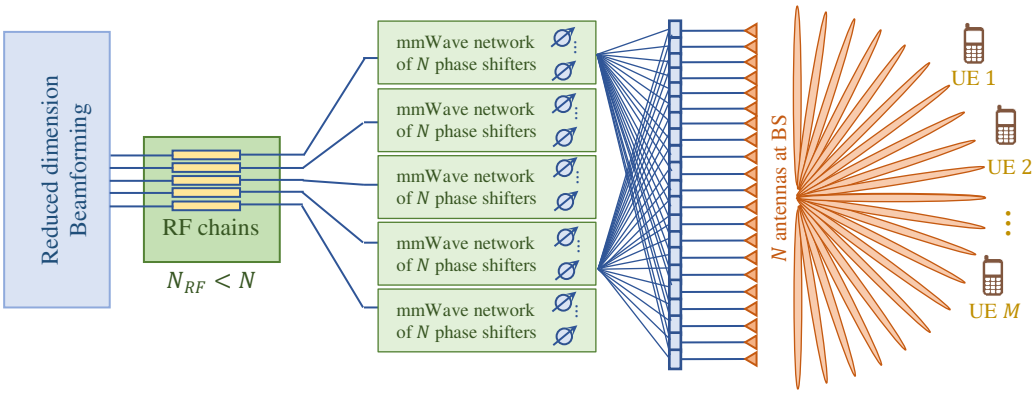

Figure 4 System model of hybrid beamforming M-MIMO using phase shifters

The comparison of the three beamforming techniques is tabulated in Table 1 [30, 28, 29]. Digital beamforming is chosen when $N_{RF} = N$, whereas for $N_{RF} = 1$, a phased array analog beamforming is desirable. However, for mmWave M-MIMO systems where $N_{RF} < N$, hybrid beamforming architecture offers the most promising choice acting as a trade-off between performance versus complexity. Hybrid beamforming can also be realized by using lens antenna array that enables direct access to the

beamspace channel. Lens antenna array computes spatial Fourier transform, transforming the conventional spatial channel into the beamspace channel.

Table 1 Comparison of various beamforming techniques

Features	**Analog beamforming**	**Digital beamforming**	**Hybrid (analog-digital) beamforming**
Number of users	Single	Multiple	Multiple
Signal control capability	Phase controlled only	Amplitude and phase controlled	Amplitude and phase controlled
Hardware requirement	Simplest; Single RF chain $N_{RF} = 1$	Most complex; RF chains in accordance to number of transmit antennas at BS $N_{RF} = N$	Medium complexity; a smaller number of RF chains is required as compared to number of antennas at BS $N_{RF} < N$
Energy consumption	Low	High	Medium
Cost	Low	High	Medium
Performance	Poor	Best	Better
Suitability for mmWave M-MIMO	Unsuitable; no amplitude control, no multi-user	Impractical; high cost and high energy consumption	Practical and realistic

3. System model

A single user downlink massive MIMO mmWave system is considered with ABF architecture in which a base station with a uniform linear array (ULA) of N_t antennas and a single RF chain communicates one data stream to a user having ULA of N_r antennas with a single RF chain as illustrated in Figure 5. The scalar baseband precoder f_{BB} followed by analog precoder $\boldsymbol{f}_{RF} \in \mathcal{F}(N_t \times 1)$ are implemented at transmitter side whereas the scalar baseband combiner w_{BB} followed by analog combiner $\boldsymbol{w}_{RF} \in \mathcal{W}\ (N_r \times 1)$ are applied at receiver side. The properties of the sets $\mathcal{F}$ and $\mathcal{W}$ are determined by specific analog hardware scheme used in analog phase shifters. The transmitted precoded signal $\boldsymbol{x}\ (N_t \times 1)$ sent to the receiver is given by $\boldsymbol{x} = \boldsymbol{f}_{RF} f_{BB} s$, where s is symbol transmitted with normalized power i.e., $\mathbb{E}\{|s|^2\} = 1$.

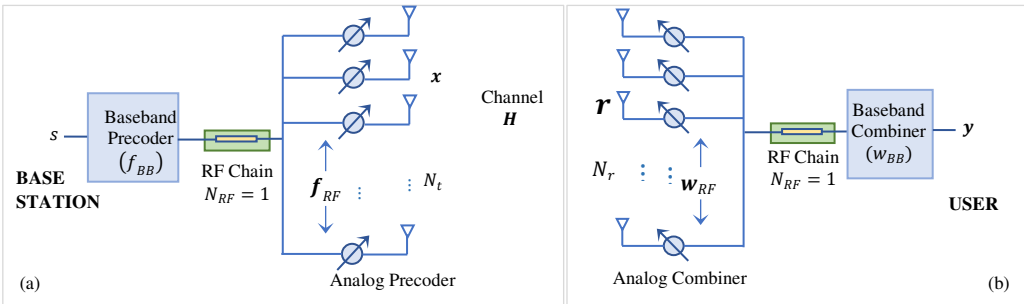

Figure 5 System model of massive MIMO mmWave system with one RF chain.

The extensively used Saleh-Valenzuela channel model has been adopted for mmWave communication in this work and the mmWave spatial channel matrix $\boldsymbol{H}(N_r \times N_t)$ between BS and user is written as

$$\boldsymbol{H} = \sqrt{\frac{N_t N_r}{\rho}} \left(\sum_{l=1}^{L} \beta^l \boldsymbol{a}_{UE}(\theta^l) \boldsymbol{a}_{BS}^H(\psi^l) \right) \tag{1}$$

where, ρ denotes the average pathloss between BS and user, β^l symbolizes complex gain and the term $\beta^l \boldsymbol{a}_{UE}(\theta^l)\boldsymbol{a}_{BS}^H(\psi^l)$ represents line of sight (LOS) path for $l = 1$ and $(l-1)$th non line of sight (NLoS) paths for $2 \leq l \leq L$, where $L-1$ is total number of NLoS paths. $\boldsymbol{a}_{UE}(\theta^1)$ is $(N_r \times 1)$ array steering vector for N_r receive antennas ULA and is given by

$$\boldsymbol{a}_{UE}(\theta^1) = \frac{1}{\sqrt{N_r}}\begin{bmatrix} 1 \\ e^{-j2\pi\theta^1} \\ \vdots \\ e^{-j2\pi(N_r-1)\theta^1} \end{bmatrix} = \frac{1}{\sqrt{N_r}}\begin{bmatrix} 1 \\ e^{-\frac{j2\pi}{\lambda}d\sin\phi^1} \\ \vdots \\ e^{-\frac{j2\pi}{\lambda}(N_r-1)d\sin\phi^1} \end{bmatrix} \tag{2}$$

where, θ^1 is spatial angle given by $(d/\lambda)\sin\phi^1$, ϕ^1 is physical direction covering one sided spatial horizon satisfying $-\pi/2 \leq \phi^1 \leq \pi/2$, λ is wavelength of mmWave signal and d is spacing between antennas, satisfying $d = \lambda/2$ at mmWave frequencies. The amplitudes of NLoS components $\{|\beta^l|\}_{l=2}^{L}$ are quite feebler than the amplitude of LoS component β^1, making mmWave channel sparse. The array steering vector $\boldsymbol{a}_{BS}(\psi^1)$ at BS can similarly be written as in equation (2).

The received signal at user is observed as $\boldsymbol{r} = \boldsymbol{H}\boldsymbol{f}_{RF}f_{BB}s + \boldsymbol{n}$, where $\boldsymbol{n}(N_r \times 1) \sim \mathcal{N}_{\mathbb{C}}(0, \sigma^2\boldsymbol{I}_{N_r})$ is additive white Gaussian noise vector. The received signal $\boldsymbol{y}$ obtained from analog combiner $\boldsymbol{w}_{RF}$ and digital combiner w_{BB} is given by $\boldsymbol{y} = w_{BB}^*\boldsymbol{w}_{RF}^H\boldsymbol{r}$. The same can be expressed as

$$\boldsymbol{y} = w_{BB}^*\boldsymbol{w}_{RF}^H\boldsymbol{H}\boldsymbol{f}_{RF}f_{BB}s + w_{BB}^*\boldsymbol{w}_{RF}^H\boldsymbol{n} \tag{3}$$

The spectral efficiency of the system R can be given as

$$R = \log_2\left(1 + \frac{\left\|w_{BB}^*\boldsymbol{w}_{RF}^H\boldsymbol{H}\boldsymbol{f}_{RF}f_{BB}\right\|^2}{\left\|w_{BB}^*\boldsymbol{w}_{RF}^H\right\|^2\sigma^2}\right) \tag{4}$$

Since a single RF chain is connected to all antennas using phase shifters, so all the elements of analog beamformers should satisfy constant modulus norm constraint i.e., $\left|[\boldsymbol{f}_{RF}]_i\right| = 1$ for $i = 1,2,\ldots,N_t$ and $\left|[\boldsymbol{w}_{RF}]_j\right| = 1$ for $j = 1,2,\ldots,N_r$ [16]. With the consideration of normalized transmit and receive power constraint i.e., $\left\|f_{BB}\boldsymbol{f}_{RF}\right\|^2 \leq 1$ and $\|w_{BB}\boldsymbol{w}_{RF}\|^2 \leq 1$ respectively, the optimal values of f_{BB} and w_{BB} for maximizing R as given in (4) become $\sqrt{1/N_t}$ and $\sqrt{1/N_r}$ respectively.

Subsequently, by applying both transmit and receive power constraints and constant modulus constraint dependent on phase shifters, the analog beamformer optimization problem can be formulated as

$$\max_{\boldsymbol{f}_{RF},\boldsymbol{w}_{RF}} \log_2\left(1 + \frac{\gamma\left\|\boldsymbol{w}_{RF}^H\boldsymbol{H}\boldsymbol{f}_{RF}\right\|^2}{N_t\left\|\boldsymbol{w}_{RF}^H\right\|^2}\right) \tag{5}$$

$$s.t. \left|[\boldsymbol{f}_{RF}]_i\right| = 1 \text{ for } i = 1,2,\ldots,N_t$$

$$\left|[\boldsymbol{w}_{RF}]_j\right| = 1 \text{ for } j = 1,2,\ldots,N_r$$

where, $\gamma = 1/\sigma^2$ denotes the signal to noise ratio (SNR)

In this work, the proposed model is for downlink, however the same model can be applied to uplink channel with replacing $\boldsymbol{H}$ by its transpose and swapping the roles of precoders $(f_{BB}, \boldsymbol{f}_{RF})$ and combiners $(w_{BB}, \boldsymbol{w}_{RF})$ with each other. The maximization of SE in (5) requires a joint optimization over the transmit beamformer $\boldsymbol{f}_{RF}$ and receive beamformer $\boldsymbol{w}_{RF}$ which is a challenging non-convex problem due to constant modulus constraint and involvement of multiple variables, and DNN has a capability to confront this problem.

4. ABF DNN architecture

In this section, the detailed design of ABF DNN is elaborated on the basis of the system model shown in figure 1. ABF DNN is constructed to generate an optimized analog beamformer vectors $\boldsymbol{f}_{RF}$ and $\boldsymbol{w}_{RF}$ based on the estimated channel $\boldsymbol{H}_e$ and SNR. Owing to imperfect CSI, BF design involves two stage DL based procedure as exhibited in Figure 6.

1. Offline training
2. Online deployment

During offline training procedure, the network learns by what means maximal SE can be achieved according to the input of channel estimate. The channel estimate $\boldsymbol{H}_e$ is estimated by mmWave channel estimator [14] from the generated simulation channel parameters $\boldsymbol{H}$. This mmWave channel estimator is employed at BS to receive the user's feedback signal by sending pilot symbols with beamformers in a hierarchical codebook.

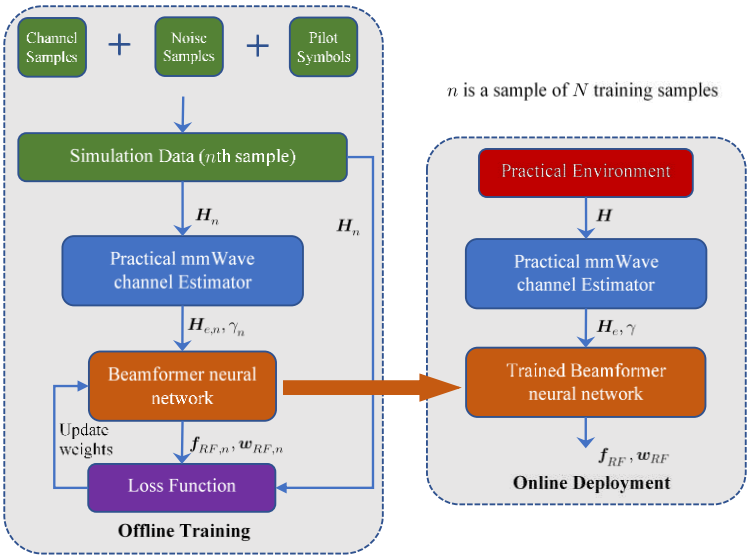

Figure 6 Illustration of two stage analog beamforming design approach.

Algorithm 1 Deep learning based analog beamforming design for massive MIMO system.

INPUT: $\boldsymbol{H}_e$(estimated channel), $\boldsymbol{H}$(perfect channel) and γ (SNR)

OUTPUT: Optimized analog precoder $(\boldsymbol{f}_{RF})$, combiner $(\boldsymbol{w}_{RF})$ and loss function (λ)

1 Initialization: The training data sets containing $\boldsymbol{H}_e \in \mathbb{C}^{N_r \times N_t}$ and $\boldsymbol{H} \in \mathbb{C}^{N_r \times N_t}$ for different combinations of N_r and N_t from [14] are imported. Here, $N_r \in 2^{\mathbb{N}}$ and $N_t \in 2^{\mathbb{N}}$.

2 γ is initialized to a single element.

3 The $Re(\boldsymbol{H}_e)$ and $Im(\boldsymbol{H}_e)$ are concatenated to a separate dimension of $\boldsymbol{H}_{est}$. So, $\boldsymbol{H}_{est} \in \mathbb{R}^{2 \times N_r \times N_t}$.

4 **MODEL:** Inputs = $[\boldsymbol{H}_e, \boldsymbol{H}, \gamma]$, output = $[\boldsymbol{f}_{RF}, \boldsymbol{w}_{RF}, \lambda]$, optimizer = `'adam'`

a. Batch normalization $(\boldsymbol{H}_{est})$

b. $\boldsymbol{H}_{est}$ is flattened to get an array of size $(1 \times (2N_r N_t))$

c. $for\left(i \text{ in} \frac{(2N_r N_t)}{2n} \forall n \in \mathbb{N}\right)$

i. $if(i = N_t)$

$\theta =$ Dense $(i$, activation = `'sigmoid'`$)$

$\phi =$ Dense $(N_r$, activation = `'sigmoid'`$)$

$break\ for$

ii. Dense $(i$, activation = `'sigmoid'`$)$

iii. Batch normalization (i)

d. $\boldsymbol{f}_{RF} = \cos(\theta) + j\sin(\theta)$

e. $\boldsymbol{w}_{RF} = \cos(\phi) + j\sin(\phi)$

f. $\lambda = -\frac{1}{N}\sum_{n=1}^{N} log_2\left(1 + \frac{\gamma_n \left\| \boldsymbol{w}_{RF,n}^H \boldsymbol{H}_n \boldsymbol{f}_{RF,n} \right\|^2}{N_t \left\| \boldsymbol{w}_{RF,n}^H \right\|^2}\right)$

5 Save model data/weights to be used while testing stage.

The proposed DNN architecture has a multi-layer structure including input layer, dense and batch normalization layers and lambda layer. Firstly, the mmWave channel estimator output $\boldsymbol{H}_e$, perfect channel $\boldsymbol{H}$ and SNR γ are given to input layer for netting the features of input data. As framed DNN is real valued, so for the input vector to be real, the real and imaginary parts of $\boldsymbol{H}_e$ are concatenated together to form a $2 \times N_t N_r$ real valued vector which is given as input to preliminary dense layer. There are three or more dense layers with decreasing order of neurons deployed in hidden layers according to the dimension of training sequence successively to generate the output neurons by means of activation functions. Here, sigmoid function defined as $f(x) = 1/(1 + e^{-x})$ is used as activation function. A batch normalization layer is always followed by a dense layer for pre-processing of input to dense layer. The self-defined end layer of DNN is lambda layer which is designed to directly enforce the constant modulus constraint in the output layer to both analog beamformers $\boldsymbol{f}_{RF}$ and $\boldsymbol{w}_{RF}$. They are originally complex valued vectors but the input to this layer is real valued vectors φ and ϑ extended from last dense layer. So, corresponding complex value output can be obtained from lambda layer using

$$\boldsymbol{f}_{RF} = \exp(j\varphi) = \cos(\varphi) + j.\sin(\varphi) \tag{6}$$

$$\boldsymbol{w}_{RF} = \exp(j\vartheta) = \cos(\vartheta) + j.\sin(\vartheta) \tag{7}$$

where, φ and ϑ are the phase of analog beamforming coefficient in $\boldsymbol{f}_{RF}$ and $\boldsymbol{w}_{RF}$ respectively.

Table 2 Implementation particulars of the analog beamforming deep neural network.

	Layer Name	**Output Dimension**	**Activation Function**	**Number of Parameters**
1×64	Input Layer	128×1		0
	Dense Layer 1	256×1	sigmoid	33024
	Dense Layer 2	128×1	sigmoid	32896
	Dense Layer 3	64×1		8256
	Lambda Layer	64×1		0
2×32	Input Layer	128×1		0
	Dense Layer 1	256×1	sigmoid	33024
	Dense Layer 2	128×1	sigmoid	32896
	Dense Layer 3	32×1		4128
	Dense Layer 4	2×1		258
	Lambda Layer 1	32×1		0
	Lambda Layer 2	2×1		0
4×64	Input Layer	512×1		0
	Dense Layer 1	512×1	sigmoid	262656
	Dense Layer 2	256×1	sigmoid	131328
	Dense Layer 3	128×1	sigmoid	32896
	Dense Layer 4	64×1		8256
	Dense Layer 5	4×1		516
	Lambda Layer 1	64×1		0
	Lambda Layer 2	4×1		0
8×64	Input Layer	1024×1		0
	Dense Layer 1	1024×1	sigmoid	1049600
	Dense Layer 2	512 ×1	sigmoid	524800
	Dense Layer 3	256×1	sigmoid	131328
	Dense Layer 4	128×1	sigmoid	32896

	Dense Layer 5	64×1		8256
	Dense Layer 6	8×1		1032
	Lambda Layer 1	64×1		0
	Lambda Layer 2	8×1		0

The optimized vectors are restructured with proper learning rate of DL on the basis of loss function. Since DNN is centred on gradient descent method, this loss function is certainly approached to a minimal correspondingly to the maximal of average SE. Loss function (λ) is directly related to objective function in equation (5) for training the analog beamformers and can be formulated as

$$\lambda = -\frac{1}{N}\sum_{n=1}^{N} log_2\left(1 + \frac{\gamma_n \left\|\boldsymbol{w}_{RF,n}^H \boldsymbol{H}_n \boldsymbol{f}_{RF,n}\right\|^2}{N_t \left\|\boldsymbol{w}_{RF,n}^H\right\|^2}\right) \tag{8}$$

where, N denotes the total number of training samples. The nth sample associated with SNR, perfect CSI, analog precoder vector and analog combiner vector are represented by γ_n, $\boldsymbol{H}_n$, $\boldsymbol{f}_{RF,n}$ and $\boldsymbol{w}_{RF,n}$ respectively.

After the completion of offline training, DNN get well trained with the conformation of minima of loss function in (8) and can be deployed online for any practical channel scenario satisfying same constraints but with lesser complexity. Therefore, the parameters of DNN essentially needs to be optimized in offline training before deploying online. During online deployment, DNN needs only to accept inputs, and it directly outputs analog beamformer vectors, as the parameters of DNN are already optimized in offline training stage. The perfect CSI $\boldsymbol{H}$ is involved only for calculating loss during offline training without any need in online deployment stage. The learning framework for ABF is explained in algorithm 1. The detailed implementation of ABF DNN structure of various MIMO system configurations and a MISO system are tabulated in table 2.

5. Simulation results

The simulation results for evaluating the performance of DL-based ABF system for various antenna configurations are provided in this section. The DNN design is constructed using `keras`, `scipy.io` and `numpy`. The various parameters considered throughout the simulations are tabulated in Table 3. Besides that, Saleh Valenzula mmWave channel model in [14] is considered with same parameters for half spaced ULA for generating 100000 simulation channel samples. The DNN has been trained in the simulations for 2000 epochs. The utilization of large number of training samples, optimal batch size, number of epochs and adoption of best learning rate attribute for excellent performance of DNN are employed as proved by Huang et al. [21].

Table 3 Values of parameters considered in simulations.

System Parameters	**Values**
Number of BS antennas	64/32
Number of antennas at user	1/2/4/8
Number of RF chains at transmitter	1
Number of RF chains at receiver	1
Number of training samples	100000
Pilot to noise power ratio	10dB
Number of paths in channel	3 (1 LoS, 2 NLoS)
Learning rate	0.00005
Optimizer	Adam
Batch size	256

The SE performance against the SNR of various configurations of analog precoding and combining as well as only analog precoding are presented in Figure 7. To validate the impact of proposed results, the result of 1×64 system with 10 dB pilot to noise power ratio by Lin and Zhu [27] is benchmarked which corresponds to 1×64 in Figure 7. It can be witnessed that from 1×64 (analog beamformer only at transmitter), 2×32 (analog beamformers at both transmitter and receiver) is superior by 38.9% and 20.4% improvement at 10dB and 20dB respectively. It can be noticed that significant gain in SE can be achieved

even with lesser number of antennas at transmitter end by installing low dimensional analog beamforming architecture at receiver end. By doing so, the complexity at transmitter also gets marginal. This implies that ABF at both transmitter and receiver side is far better than standalone ABF at transmitter side.

Furthermore, this improved performance can be more apparent by using large configurations of multiple antennas. Various antenna configurations were considered to demonstrate the effectiveness of ABF at both ends. It can be seen from Figure 7 that 4×64 shows enhancement from 2×32 of 112% and 65.4% whereas 8×64 outperforms from 4×64 of 32.7% and 24.17% at 10dB and 20dB respectively. It can also be deduced that by further increasing number of antennas does not yield equivalently increase in SE as observed with rise in lower number of antennas.

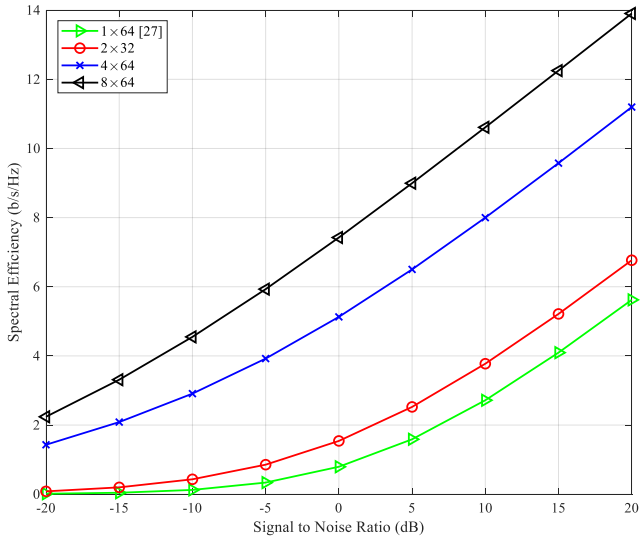

Figure 7 Simulation results of spectral efficiency versus signal to noise ratio in the case of analog precoding $[1 \times 64]$ and various configurations of analog precoding and combining $[2 \times 32,\ 4 \times 64, 8 \times 64]$.

6. Conclusion

The DL approach is inherited in proposed ABF with large scale antennas in mmWave channel system to enhance system performance. The proper design of lambda layer and loss function works satisfactory with imperfect CSI as well. In this work, the number of layers and associated neurons to each layer are depicted by empirical trials. This DNN model can work effectively on any online deployment whose channel conditions do not match with those employed in training stage. For more rigorous analysis, multiple users ABF or HBF designs can also be regarded for future work and further exploration will be a call to validate the productiveness of DL networks.

Conflicts of Interest

The authors declare no conflict of interest.

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