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Deep Learning Algorithm for Optimal Hybrid Precoder for mmWave Massive-MIMO in WBAN

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Abstract

Hybrid precoding technique reduce the complexity and provides better performance by providing acceptable throughput in the system..In this paper, we have used a neural network to conduct hybrid phased-Zero forcing with poor phase shifter resolution for improved spectral efficiency (HPZFNN). Finally, we have compared performance of the proposed systems to that of the existing system. Simulation results indicate that the HPZFNN hybrid pre-coder architecture method outperforms other approaches with low phase shifter resolution in terms of spectral accuracy. This paper attempts to contribute towards the development of a fifth-generation (5G) wireless infrastructure for ultra-dense networks by providing improved local area (ELA) mm Wave technologies

Keywords*: Deep learning Algorithm, Water-filling Algorithm, optimal hybrid precoder, mm wave Massive-MIMO, WBAN*

1. Introduction

Wireless data traffic is expected to rise 1000-fold by 2021 and over 10,000-fold by 2030, necessitating the need to introduce 5G technologies to deal with the exploding data generation, storage, and transmission [1]. The usage of underutilized bandwidth in ultra-high-frequency bands, such as the millimeter-wave (mmWave) band, has recently piqued the attention of the scientific community as one of the most effective ways to satisfy 5G specifications [2]. One of the evolutionary advancements showed in mmWave networking is the ten-fold rise in carrier frequency compared to current wireless networks. In other terms, mmWave signals increase free-space path loss by orders of magnitude [3]. The mmWave MIMO method, inspired by massive multiple-input multiple-output (MIMO), is regarded as a possible technique for high system throughput. Hybrid precoding is a method to multiplex a huge number of data streams and achieve more precise beamforming in mmWave massive MIMO[1]. Gao et al. [4] explored a sequential intervention cancellation-based hybrid precoding system with low complexity was proposed, which split the sum-rate optimization problem with non-convex constraints into many sub-rate optimization problems. The researchers then configured a hybrid precoder to create a low-complexity hybrid analog/digital precoding for multiuser mmWave systems in Alkhateeb et al., [5]. However, because the previously introduced hybrid analog/digital precoding methods are based on singular value decomposition (SVD), these precoding techniques have a high level of disturbance and needs improved allocation method. Furthermore, although the recently proposed geometric mean decomposition

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(GMD)-based scheme given by Chen et al., [6] can solve the bit allocation issue, it still faces significant challenges in dealing with the non-convex restriction on the analogue precoder and leveraging the structural characteristics of mmWave large MIMO systems.

Many researchers have recognized this gap in recent years. They have proposed various methods for reducing computational complexity or improving precoding efficiency, including the (GMD)-based scheme [6], the matrix factorization-based hybrid precoding mean explained by Jin et al., [7], a precoding method based on radio-frequency (RF) and baseband signal processing discussed by Zhang and Huang [8], and hybrid spatial processing architecture. Even though a lot of research has improved the hybrid precoding efficiency in mmWave large MIMO systems, there are still a lot of issues, and two of the biggest ones are the extremely high computational complexity and low machine performance. An alternating minimization scheme for effectively modeling hybrid precoder was also supported by Yu et al. [10] to achieve high spectrum performance with low complexity. Chen et al. [11] proposed a beamspace-SVD dependent hybrid precoding approach for reducing uncertainty by using low-dimensional beamspace channel state information (CSI) interpreted by compressive sensing (CS) detectors. In general, these works depend on traditional mathematical methods such as the SVD and GMD, which are insufficient to manipulate the mmWave huge MIMO's sparsity statistics. Simultaneously, since conventional approaches fail to take advantage of the structural properties of such mmWave devices, traditional low-complexity schemes are implemented at the expense of the systems' hybrid precoding. In the MIMO-OFDM scheme, He et al. [12] used a linear and Gaussian interpolation algorithm to reduce the feedback overhead induced by beam formation on each subcarrier. The actual model that explains the relationship between BER and SNR with limited input, on the other hand, has yet to be established. Duel-Hallen et al. [16] described and tested a long-range fading channel prediction algorithm for simulating stationary fading models using calculated data and data produced by a physical channel model. They calculate the average BER for a given SNR using an estimated formula they created. Hassan [14] looked at how orthogonal frequency division multiplexing (OFDM) is used in radio communications to reduce inter-symbol conflict and improve device capability. By developing STCP estimators for a 2x2 multi-antenna device using MATLAB, they could compare MIMO-OFDM using BPSK and QAM on Rayleigh and Rician networks. As a result, previous work has failed to address these issues fundamentally, and new approaches for improving the hybrid precoding efficiency of mmWave massive MIMO are urgently needed. Deep learning by Hinton et al. [15], showed a new solution that has recently emerged is a truly remarkable technique for dealing with massive amounts of data and solving complex nonlinear problems. Deep learning has been demonstrated to be an excellent method for dealing with challenging non-convex problems and high-computation questions, thanks to its superior recognition and representation skills. Beam selection, heterogeneous network, non-orthogonal multiple access (NOMA), huge MIMO, and heterogeneous network are several previous works that have explored deep learning in communications [16–21]. Deep learning has already been extended to intelligent traffic management [22–25], demonstrating significant advances resulting from deep-learning-based connectivity schemes. As a result, this research looks at a process that combines deep learning with hybrid precoding in mmWave MIMO systems.

This paper proposes a deep-learning-enabled mmWave massive MIMO architecture for efficient hybrid precoding. Each precoder choice for obtaining the best decoder is treated as a mapping connection in the deep neural network (DNN). The hybrid precoder is chosen for improving the precoding phase of

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the mmWave huge MIMO by training focused on the DNN. There are various application cases for typical deep learning algorithms, as we saw in the previous section's associated works. In this paper, we have used the proposed hybrid BiLSTM neural network with channel characteristics and the Fast Fourier Transform (FFT) technique to resolve these issues [26], where we use FFT to preprocess the data collection, allowing us to spot deviations that aren't detectable throughout the established time domain. We have used a bidirectional LSTM (BiLSTM) to encode sentence-level content, concatenated with a CNN-extracted local lexical function, to predict whether an object serves as an argument in a sentence. Bidirectional recurrent neural networks (RNN) are just two separate RNNs joined together. This configuration allows the networks to supply both backward and forward knowledge about the chain at any one time. Using bidirectional transfer of inputs in two directions, one from past to future and the other from future to past.A hybrid precoding transceiver design, which combines a digital and analogue precoder, has lately attracted a lot of interest as a cost-effective option. The difference between this technique and unidirectional is that in the LSTM that operates backward, knowledge from the future is preserved while using the two hidden states together, we will retain information from both past and future at any point in time.

1. Proposed System

For this work, consider medical results, such as pulse rate, blood pressure, glucose content, and temperature, as input to the data stream. We combine IFFT and parallel to serial conversion with a hybrid pre-coding scheme (phased-Zero forcing). BiLSTM neural network is designed having wireless channel characteristics to predict the channel parameters. Finally, to obtain an output stream, execute serial to parallel conversion and FFT[26]. Analyze the proposed system's output using the flow diagram as shown in Fig 1.

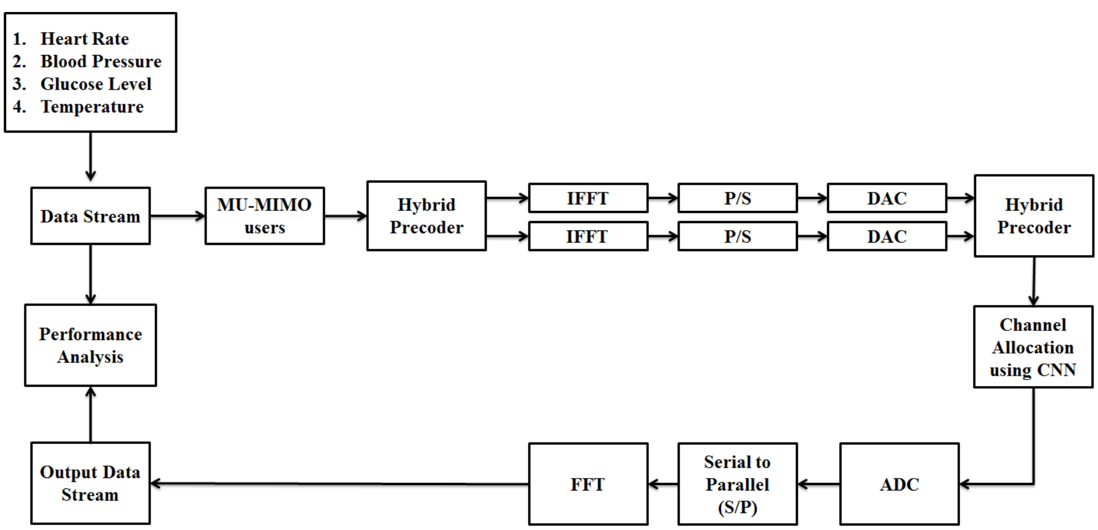

Fig 1. Flow Diagram of hybrid pre-coding scheme (phased-Zero forcing) process

2.1 Schematic Module Representation

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- Data Selection and Loading: Consider medical data as the input for the data stream, such as heart rate, blood pressure, glucose level, temperature.
- Pre-Coding Scheme: Perform a hybrid pre-coding scheme (phased-Zero forcing) process and IFFT and parallel to serial conversion. Fourier analysis converts a signal from its original domain (often time or space) to a representation in the frequency domain and vice versa.
- Channel Selection: A Bidirectional LSTM, or biLSTM, is a sequence processing model that consists of two LSTMs: one taking the input in a forward direction and the other in a backward direction : It performs serial to parallel conversion and FFT to obtain output stream[26]

2.2 Enhanced Approaches

We provide simulation findings to verify the proposed scheme's excellent success in the deep Learning algorithm under mm-wave Massive-MIMO in WBAN using optimal hybrid precoder. To deal with this massive growth in wireless data traffic, one solution is to boost spectrally efficient networks like 4G LTE in bands below 6 GHz by using more sophisticated spectral performance strategies such as textual attribute analysis utilizing deep learning algorithms. It is evident that to keep up with the ever increasing wireless data consumption, significant hardware change need to be acknowledged towards implementation of optimal hybrid precoder .The second solution is to increase the frequency and enter an unused nontraditional range of vast bandwidths(such as millimeter wave mmWave bandwidth , 2GHz) allows for basic air interfaces rather than highly sophisticated methods designed to achieve high spectral performance for narrower bandwidths. Furthermore, as data demands grow, mmWave systems can easily evolve to even higher channel capacities and there will be plenty of beam spacing to boost spectral performance.

2.3 System Model

In this section we provide the channel models of mmWave MIMO systems, which would then be formulated as a matrix factorization factor using hybrid precoding design. Owing to the enormous number of radio-frequency (RF) chains in mmWave MIMO systems with tens to hundreds of antennas, full-digital precoders are unfeasible due to the manufacturing cost and energy consumption of high-frequency mixed signal components. Furthermore, a few notations on complex matrix derivatives are introduced shortly.

This paper adopted the following notations: For vectors, matrices, or sets accordingly, boldface lowercase letters, boldface uppercase letters and calligraphic story lines are utilized. The real or complicated fields are listed **R** and **C**, respectively. The superscripts $(\bullet)^T$. $(\bullet)^*$ and $(\bullet)^H$ stand for transpose, conjugate, and conjugate transpose operations, respectively $tr(\bullet)$ is the trace of a matrix; $\|\bullet\|$ denotes the Euclidean norm of a vector; $\|\bullet\|F$ represents the Frobenius norm of a matrix; $\mathrm{I}(\bullet)$ represents the mutual information. The linear precoder is divided into analog or digital precoders, who were implemented alternately in analog and digital areas. A small number of RF chains is made of both the digital precoder, whereas phase shifters are used for the analog precoder. Each analog precoder entry fulfills the constant modulus limit because of the feature of phase shifters. Such continuous module restrictions provide an important obstacle throughout the development of hybrid precoding.

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Assume a mmWave MIMO point-to-point system, in which a N_t-antennas transmitter provides N_s data streams to a N_r-antenna recipient. N_{rf} is the number of RF chains on the transmitter that fulfills $N_s \leq N_{rf} \leq N_t$. They take into account the hybrid precoding approach that first precodes N_s data streams that used a digital precoder and thereafter analog precoding. The baseband signal received $y \in C^{N_r \times 1}$ can be written as

$$y = HF_{RF}F_{BB}x + n \tag{1}$$

Where $H \in C^{Nr \times Nt}$ is the channel matrix $F_{RF} \in \mathrm{F}^{N_t \times N_{rf}}$ is the analog precoder with $\mathrm{F} = \left\{ f \middle\| f \right| = \frac{1}{\sqrt{N_t}} \}$ being the constant modulus set; $F_{BB} \in \mathrm{C}^{N_{rf} \times N_s}$ is the digital precoder $x \in \mathrm{C}^{N_s \times 1}$ is the input data vector and $n \in \mathrm{C}^{N_t \times 1}$ is really the circular symmetrical complex independent and equitably represented (i.i.d). Zero media and value of traditional Gaussian noise $\sigma^2 I$ Provide that whilst the transmitter and even the recipient are known along channel H and each element including its input data vector x is gets uniformly dispersed without cardinality M from such a specified constellation. Therefore mutual service is transmitted either by input-output [27]

$$\mathrm{I}(x;y) = N_s \log M = \frac{1}{M^{N_s}} \sum_{m=1}^{M^{N_s}} E_n \left\{ \log \sum_{k=1}^{M^{N_s}} e^{-d_{mk}} \right\} \tag{2}$$

Where $d_{mk} = \sigma^{-2} \left(\left\| HF_{RF}F_{BB}\left(x_m - x_k\right) + n \right\|^2 - \left\| n \right\|^2 \right.$ with xm and xk being two possible input data vectors from x.

a. Channel Model

Standard Multipath Models may be used for the mmWave MIMO channel. Assume the number of pathways between it transmitter and or the recipient L of physical propagation. The three parameters of each route are specified: complexgain α_i , angle of arrival $\theta_{r,i}$ ` and angle of departure $\theta_{t,i}$ .. The angles $\left\{\theta_{r,i}\right\}_{i=1}^{L}$ and $\left\{\theta_{t,i}\right\}_{i=1}^{L}$ are i.i.d. uniformly distributed over [0, 2□) and the complex gains $\left\{\alpha_i\right\}_{i=1}^{L}$ are i.i.d. complex Gaussian distributed in unit variance without zero-mean. The channel matrix H gets given using that same model [28]

$$H = \sqrt{\frac{N_r N_t}{L}} \sum_{i=1}^{L} \alpha_l \mathrm{a}\left(\theta_{r,i}\right) \mathrm{a}\left(\theta_{t,i}\right)^H \tag{3}$$

Where $\mathrm{a}\left(\theta_{t,i}\right)$ and $\mathrm{a}\left(\theta_{r,i}\right)$ Arrays provide transmission steering vectors while antenna arrays typically received. This paper contains uniform linear frames for said transmitter and receiver which steering vector array $\mathrm{a}\left(\theta\right)$ is given by

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$$\mathrm{a}(\theta)=\frac{1}{\sqrt{N}}\left[1,e^{-j\frac{2\pi}{\lambda}d\sin\theta},....,e^{-j\frac{2\pi}{\lambda}d(N-1)\sin\theta}\right]^{T} \tag{4}$$

where N is the number of antenna element, □is the wave length of the carrier frequency and $d=\frac{1}{2}\lambda$ is the antenna spacing.

The channel in (3) can be rewritten in a more compact form as

$$H-A_r\mathrm{diag}(\alpha)A_t^H \tag{5}$$

Where $\alpha=[\alpha_1,....\alpha_L]^T$, $A_r\in\mathrm{C}^{N_r\times L}$ and $A_t\in\mathrm{C}^{N_t\times L}$ are array steering matrices with constant modulus entries, given by

$$\mathrm{A_r}=\left[\mathrm{a}(\theta_{r,1}),......\mathrm{a}(\theta_{r,L})\right] \tag{6}$$

$$\mathrm{A}_t=\left[\mathrm{a}(\theta_{t,1}),......\mathrm{a}(\theta_{t,L})\right] \tag{7}$$

Note that A_t is a full rank matrix when the angels $\{\theta_{t,i}\}_{i=1}^{L}$ substantially distinct[1], and probably because this event happens $\{\theta_{t,i}\}$ is drawn from either the uniform distribution separately. Accordingly, A_r and diag(□)Full rank matrices are now one without likelihood. The rank of H is indeed determined

$$\mathrm{rank}(H)=\min\{L,N_r,N_t\} \tag{8}$$

The maximization of input-output information by power & constant modulus restrictions seems to be a fundamental approach there in hybrid precoding design. If the mmWave receiver may decode data optimally with the signal received, then perhaps the hybrid issue is phrased

$$\begin{aligned}&\underset{F_{RF}\in u,F_{BB}}{\text{Maximize}} && \mathrm{I}(x;y)\\ &\text{Subject to} && tr\left(F_{BB}^{H}F_{RF}^{H}F_{RF}F_{BB}\right)\le P\end{aligned} \tag{9}$$

Where $\mathrm{I}(x;y)$ is the transmitting power constraint P is specified in (2) and $u=\mathrm{F}^{N_t\times N_{rf}}$ is the analog precoders set seems feasible. It really is difficult to solve (9) two reasons directly: First, issue 9 is nonconvex so because two are nonconvex $\mathrm{I}(x;y)$ and U are not convex or concave as far as (F_{RF};F_{BB}). Second, this objective function is evaluated by iterative problem algorithms, $\mathrm{I}(x;y)$ this might be very expensive even though in every iteration $\mathrm{I}(x;y)$ No expressions in closed form.

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In response to this demand and improve precoding design, they propose the following formulations for matrix factoring,[29] in which the unconstrained ideal precoder is approximated with hybrid precoders (F_{RF};F_{BB}) F_{opt}, i.e.,

$$\begin{aligned} &\underset{F_{RF}\in u, F_{BB}}{\text{Minimize}} \quad \left\| F_{opt} - F_{RF} F_{BB} \right\|_F^2 \\ &\text{Subject to} \quad tr\left(F_{BB}^H F_{RF}^H F_{RF} F_{BB} \right) \leq P \end{aligned} \tag{10}$$

The unconstrained optimal precoder Fopt is given by [27, 30]

$$F_{opt} = \underset{\mathrm{F}\in F}{\text{Maximize}} \quad \mathrm{I}(x; y) \tag{11}$$

Where $F = \left\{ \mathrm{F} \middle| tr\left(\mathrm{F}^H \mathrm{F} \right) \leq P \right\}$

b. *Preliminaries on Complex Matrix Derivatives*

Non-linear optimization using complex matrix variables are also the issues examined in this study, hence they give certain concepts for complex matrix derivatives. For a univariate function $f(x): \mathrm{C} \to \mathrm{R}$ the definition of the complex derivative is given in [31]:

$$\frac{\partial f}{\partial x} \overset{\Delta}{=} \frac{1}{2}\left[\frac{\partial f}{\partial \Re(x)} - j \frac{\partial f}{\partial \Im(x)} \right] \tag{12}$$

$$\frac{\partial f}{\partial x^*} \overset{\Delta}{=} \frac{1}{2}\left[\frac{\partial f}{\partial \Re(x)} + j \frac{\partial f}{\partial \Im(x)} \right] \tag{13}$$

For a multivariate function $f(X): \mathrm{C}^{n \times r} \to \mathrm{R}$ the partial derivatives with respect to X and X* are matrices

$$\frac{\partial f}{\partial X} \overset{\Delta}{=} \left[\frac{\partial f}{\partial X_{kl}} \right] \text{ and } \frac{\partial f}{\partial X^*} \overset{\Delta}{=} \left[\frac{\partial f}{\partial X_{kl}^*} \right] \tag{14}$$

Where X_{kl}` denotes the *(k; l)*-th element of X. In addition, the complex gradient matrix $\nabla_x f(X)$ is defined as

$$\nabla_x f(X) \overset{\Delta}{=} \frac{\partial f}{\partial X^*} \tag{15}$$

Let $X_1 \in \{X, X^*\}$ and $X_2 \in \{X, X^*\}$ then the complex Hessian of f(X) with respect to X_1 and X_2 is defined in[31]:

$$H_{X_1, X_2} f \overset{\Delta}{=} \frac{\partial}{\partial vec^T(X_1)} \left[\frac{\partial f}{\partial vec^T(X_2)} \right]^T \tag{16}$$

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The number of physical propagation paths is set as L = 8,and the signal-to-noise ratio (SNR)= $\frac{P}{\sigma^2}$ is described as SNR. We generate N=1000 channel performance using (3), and then using the following average Gaussian inputs can assess system performance:

$$\frac{1}{N}\sum_{i=1}^{N}\log\det\left[1+\sigma^{-2}\mathrm{H}_i\mathrm{Q}_i\mathrm{H}_i^H\right] \tag{17}$$

Where Hi is the ith channel realization, and $\mathrm{Q}_i = F_{RF}^{(i)}F_{BB}^{(i)}(F_{BB}^{(i)})^H(F_{RF}^{(i)})^H$ with $(F_{RF}^{(i)}.F_{BB}^{(i)})$ the appropriate analog and digital precoder solution Hi. Researchers establish a benchmark again for performance of unconstrained optimum precoders and then compare our suggested approach. It addresses an overall problem of factoring of the modulus matrix. Let suggest first designing a digital analog precoder $\mathbf{F}_{\mathrm{RF}}$

$$\underset{F_{RF}\in u, F_{BB}}{\text{Minimize}} \quad \left\| F_{opt} - F_{RF}F_{BB} \right\|_F^2 \tag{18}$$

Thus it is interesting to assess the performance every arbitrary provided matrix of our suggested algorithm Fopt. The results of the method are assessed by the average error in uclidean provided as

$$\frac{1}{N}\sum_{i=1}^{N}\left\| F_{opt}^{(i)} - F_{RF}^{(i)}F_{BB}^{(i)} \right\|_F^2 \tag{19}$$

Where $F_{opt}^{(i)} \in \mathrm{C}^{N_t\times N}$, $F_{RF}^{(i)} \in \mathrm{C}^{N_t\times N_{rf}}$ and $F_{BB}^{(i)} \in \mathrm{C}^{N_{rf}\times N_s}$ are outputs ofAlgorithm 1 with the given input $F_{opt}^{(i)}$ $=p_s^{m,n}$, after assuming this as optimal value of phase shifter $p_s^{m,n}$.

c. Water-filling Principle

In a frequency-selective channel, water filling and link adaptation based on CSI may be used to optimize the cumulative rate given a transmission power. Traditional water-filling, is not the ideal method for achieving efficient and dependable subcarrier power distribution. The suggested method outperformed the water-filling method. To decrease the computing complexity of [33], a new energy-efficient method was suggested in [32]. Energy-optimal link adaptation and resource scheduling methods were developed in closed forms, taking into account temporal average bit-per-Joule metrics.

For multicarrier loading issues, a water-filling method was used here. Maximize the total bit rate R_{total} for the whole multichannel MIMO-OFDM transmission system, while maintaining a constant Pt and an optimum allocation of the total transmit power P_t across the N sub-channels. This phenomenon, in contrast to the suggested system, may be expressed as:

$$K_c = p_t + \frac{\sigma_i^2}{|H_i|} \qquad 1\leq i\leq N \tag{20}$$

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Where p_i is the transmission power, σ_i^2 is the noise variance (power) and $|H_i|$ magnitude response at subchannel i respectively.To be exact, for each subchannel, the sum of transmit power and noise variance (power) scaled by the inverse of the channel (subchannel) magnitude response should be kept constant. It's also possible to write it as;

$$K_c = p_i + \frac{1}{(SNR)_i} \quad 1 \leq i \leq N \tag{21}$$

$$\text{Where } (SNR)_i = \frac{|H_i|^2}{\sigma_i^2} = \frac{P}{\sigma_i^2} \tag{22}$$

In the water-filling process, we establish all streams to be of equal significance and the SNR is defined as $\frac{P}{\sigma_i^2}$ another benefit of the suggested method is that the value of the constant Kc is computed systematically and provided below as the equation is being derived.

$$K_c = P_{avg} + \frac{1}{N}\sum_{i=1}^{N}\frac{1}{(SNR)_i} \tag{23}$$

Where P_{avg} is the average transmit power per subcarrier and $(SNR)_i$ is the signal-to-noise ratio of the subcarrier (21). Equation (23), on the other hand, will be used to determine the throughput of this loading method, while Equation (24), on the other hand, will be used to find the power vector P by using the water-filling process (1). Hence Algorithm 1 with the given input $F_{opt}^{(i)} = p_S^{m,n}$=R, after assuming this as optimal value of phase shifter $p_S^{m,n}$

$$R = \frac{1}{N}\sum_{i=1}^{N} r_1 = \frac{1}{N}\sum_{i=1}^{N}(\log_2(M))R_{c,i} = \frac{1}{N}\sum_{i=1}^{N}(p_i \propto, Qos_i) = \frac{1}{\sqrt{N}}\sum_{i=1}^{N}(p_i \propto, Qos_i) = p_s^{m,n} \tag{24}$$

The water filling algorithm and all hybrid precoding algorithm in this subsections employ the same as F_{opt} for analog and digital precoders. The unconstrained optimum precoder F_{opt} was also available under Gaussian inputs. The optimal value of phase shifter $p_S^{m,n}$ between the m-th user and the n-th channel,

$$p_S^{m,n} = \frac{1}{\sqrt{N_K}} e^{j \arg (P_M^{m,n}, P_{A^H})} \tag{25}$$

Where $P_M^{m,n}$ - digital precoding matrix for m-th user and the n-th channel; P_{A^H} – Analog precoding matrix for channel coefficient.Power allocated by individual channel is given by

$$\text{Power allocated} = \frac{P_t + \sum_{i=1}^{n}\frac{1}{H_i}}{\sum Channel(H_c)} - \frac{1}{H_i} \tag{26}$$

Where Pt is the total power of the MIMO system, which is distributed over the various channels, and Hc denotes the system's channel matrix. The algebraic sum of the capacities of all channels gives the capacity of a MIMO:

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$$Capacity = \sum_{i=1}^{n} \log(1 + \text{Power Allocation} \times H_c) \tag{27}$$

The total amount of bits that must be transmitted must be as high as possible. The water filling algorithm is carried out using the procedures outlined in the scheme. As long as the channel matrix is accessible, it may be used in both the mmWave sparse scattering channel and the traditional i.i.d Rayleigh channel.

2.4 Enhanced Channel Prediction Algorithm

Algorithm 1: Phased-ZF precoding based DNN approach in Massive MIMO

Input: Channel Matrix H_C, Maximum transmitted power Tr_{pw}, number of iteration $Iter_{no}$

Output: Precoding matrix P_A

Initialization $N_K = N_T/N_R$

1. Compute digital precoding matrix
$$P_M = \Delta\, P_A \tag{28}$$
$where,$
$\Delta -$ Power allocation matrix achieved by water filling algorithm [as given in (26)]
P_A – Analog matrix.
2. Construct the proposed DNN based on BiLSTM framework.
3. Perform the network model simulator to simulate wireless channel with artificial distortion or noise.
4. While $i \leq Iter_{no}$ do
   - (error≥τ) : Train the DNN by processing the SGD with momentum
   τ - threshold value for loss factor
   - Update fixed digital pre coding matrix. P_M
   - The optimal value of phase shifter $p_s^{m,n}$ between the m-th user and the n-th channel,
   $$p_s^{m,n} = \frac{1}{\sqrt{N_K}} e^{j \arg(P_M^{m,n}, P_{A^H})} \tag{29}$$
   $P_M^{m,n}$ - digital precoding matrix for m-th user and the n-th channel
   P_{A^H} – Analog precoding matrix for channel coefficient
   end while

2. Results and Discussion

To begin with, we study the spectral efficiency of various methods where the number of RF chains equals the data streams i.e $N_t=N_r=N_k$. Fig 2 provides the spectral efficiency obtained as a function of SNR (dB). On comparison, it is seen spectral efficiency is improved with the existing approach. It was found that the

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proposed system based on phased-ZF precoding DNN provides maximum efficiency of approximately. 98.5% at SNR =25dB compared with other schemes.

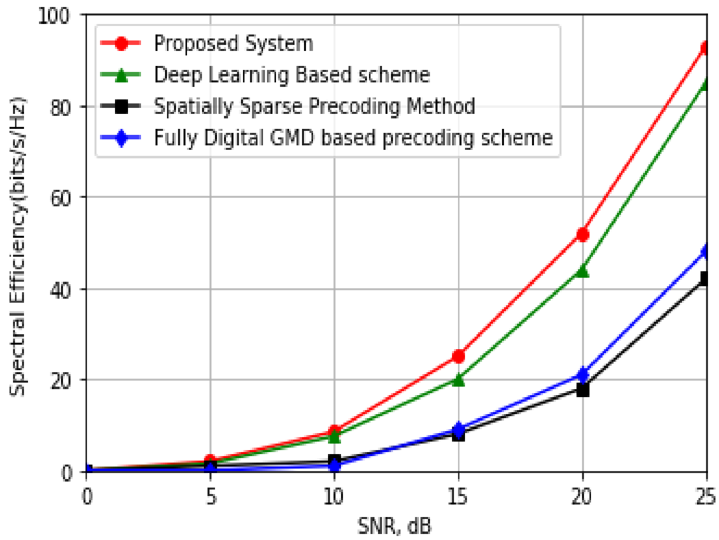

Fig. 2. Comparative plots for spectral efficiency as a function of SNR (dB)

Fig 3 shows the bit error ratio in relation to SNR (dB), and we used the proposed methodology for all system models (OFDM – no CP, OFDM, and FBMC). Using the phased-ZF precoding DNN, OFDM – no CP provided Bit Error Ratio of 10^{-2} at SNR= 30 dB , while that of OFDM and FBMC ranged from 10^{-2} to 10^{-3}. As there are a linear number of phase shifts, fully integrated structure would significantly increase power usage as N_t. It is seen that the power consumption has grown considerably more rapidly than that of the spatial multiplexing, causing the energy efficiency to fall significantly.

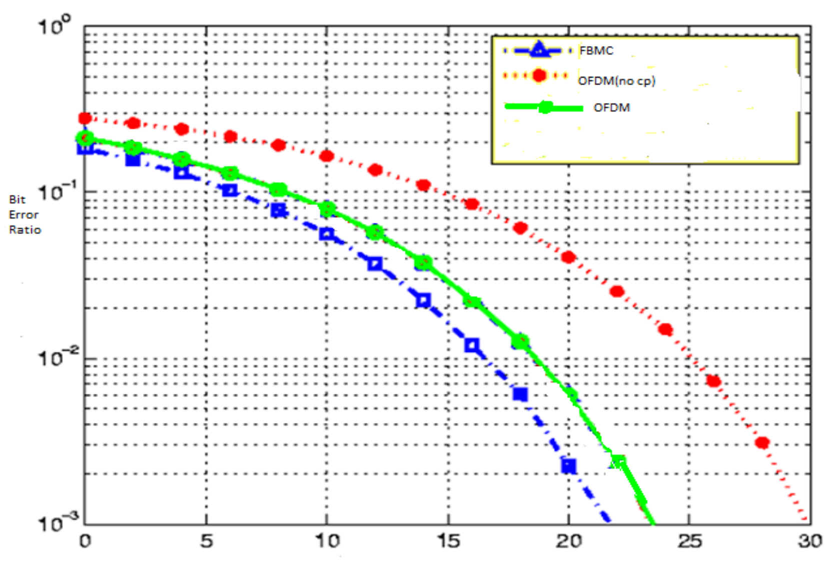

Fig. 3. Bit Error Rate performance v/s SNR for different system models

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Fig 4 shows the channel capacity obtained in the proposed system using a deep learning algorithm. The response curve shows steady increasing order of the capacity of the proposed system for SNR ranging from 6.5 to 15 dB. However, below 6.5dB or for SNR > 15db there is no significant change in the capacity of the system. Therefore, SNR working range can be defined as 6.5 to 15dB.

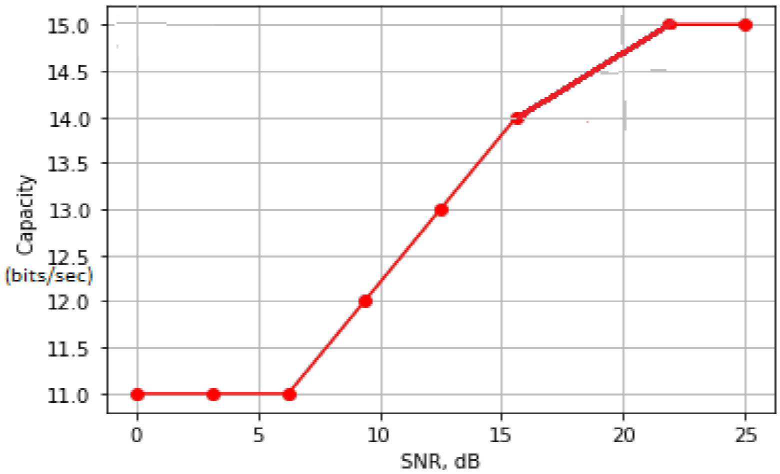

Fig. 4. Estimation of channel capacity for proposed system v/s SNR

The channel capacity as a function of SNR for different values of sub channels is as shown in Fig 5. It is seen from the curves that the dynamic range of the capacity increases with increase in the number of subchannels. For example: For 15 sub channels, the capacity changes by 9 Mbps (range is 5 to 14 Mbps); For 45 subchannels it is 20 Mbps (from 25 to 45Mbps). This is because of the insufficient interference cancellation. Therefore, depending on the capacity range requirement, optimum number of sub channels can be chosen.

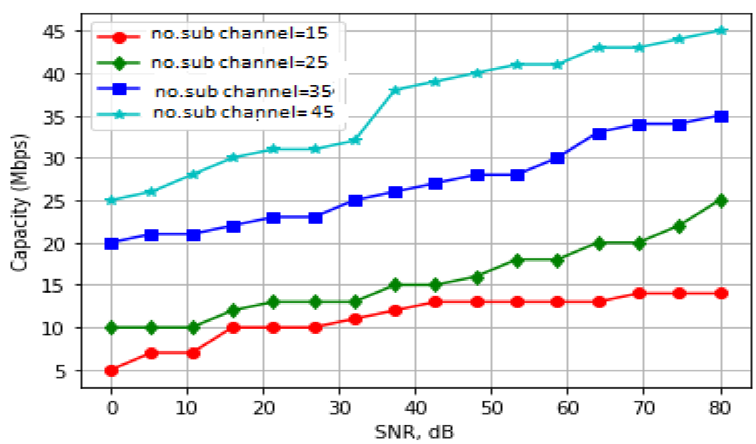

Fig. 5 Comparison of Channel Capacity v/s SNR at different sub channels (15, 25, 35, 45)

3. Conclusion

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We can conclude that using a deep learning algorithm, we can improve hybrid precoding efficiency by reducing computational sophistication and exploiting the spatial statistics of mmWave MIMO systems. The proposed method which is built on phased-ZF precoding DNN has a maximum performance (bits/Hz) of approximately 98.5 percent at a SNR of 25 dB, which is higher than that provided by the existing system. DNN-based method is capable of lowering the BER and increasing the spectrum efficiency of the mmWave as well as s achieving better output in hybrid precoding than traditional schemes thus significantly reducing the necessary computational factors. In future the new deep learning architecture can be combined with 5G standards for further signal processing in WBAN.

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