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Optimizing channel capacity for B5G with deep learning approaches in MISO-NOMA-HBF and BFNN

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ABSTRACT

This study proposes the integration of a beamforming neural network (BFNN) and multiple-input single-output based non-orthogonal multiple access (MISO-NOMA) with hybrid beamforming (HBF) for cell edge users (CEU) in a millimeter wave (mmWave)-based beyond 5G cellular communication system. This system is referred to as MISO-NOMA-HBF-BFNN. The proposed scheme has been implemented to support multiple users simultaneously and also to considerably enhance and significantly improve the overall the sum channel capacity (SC) and user channel capacities. Additionally, the simulation results demonstrate the superiority of the proposed MISO-NOMA-HBF-BFNN scheme over the existing MISO-NOMA with HBF and MISO-OMA with HBFBFNN based schemes in terms of user capacities and SC.

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1. INTRODUCTION

Non-orthogonal multiple access (NOMA) has drawn significant attention in the domain of beyond 5G (B5G) cellular communication systems [1], [2]. Existing orthogonal multiple access (OMA) techniques, including TDMA/FDMA/CDMA, may encounter significant obstacles when implemented beyond 5G (B5G) cellular communication systems due to the restricted availability of resources (time/frequency/code) [3]. The sum capacity (SC) and user capacities of OMA-based cellular communication systems can be diminished by the additional resource utilization. However, the power domain NOMA can mitigate this issue. Additionally, NOMA and millimeter wave (mmWave) systems offer a solution for B5G cellular communication. This is due to the fact that mmWaves can support ultra-high channel capacities, while NOMA can simultaneously support multiple access for multiple users [4]. However, challenges such as restricted resources and incomplete channel state information (CSI) continue to exist, requiring inventive approaches to improve user capabilities and aggregate SC.

Prior research has investigated the augmentation of channel capacity via power domain downlink NOMA, employing methodologies such as successive interference cancellation (SIC) [5]. The integration of NOMA with mmWave technology has demonstrated potential in the realm of B5G cellular communication. This approach capitalizes on the exceptionally high capacities offered by mmWave and NOMA's capability to accommodate several users concurrently [6]. Again, study shows [7] hybrid beamforming (HBF) has been recognized as a viable option for mmWave systems; yet, traditional approaches encounter constraints when it comes to facilitating multiuser access. The optimization of analog precoders in HBF systems presents considerable difficulties [8], [9] because existing methods assume perfect CSI. Accurate optimization of analog precoders is hindered by imperfections in CSI estimate, which arise from factors such as user mobility and hardware restrictions [10]. In addition, analog precoders have a limited pre-defined codebook, hence manifold optimization, element-wise iterative algorithms, and analog beamformer optimization techniques have been proposed in previous research [11]. Recent research indicates that the utilization of deep learning (DL) methods, namely beam forming neural networks (BFNN), has the potential to enhance the performance of analog precoders in the presence of suboptimal CSI conditions [12]. This is particularly relevant for cell edge users (CEUs), as it can lead to improved user capacities and system capacity. Hence, BFNN can optimize the analog precoder of the multiple-input single-output based non-orthogonal multiple access (MISO-NOMA), HBF scheme depending on the imperfect CSI, channel condition, and the SINR of CEU to improve the user capacities as well as SC [13].

Hence, the emergence of NOMA has attracted considerable interest due to its potential to offer high data rates to numerous users, especially within the framework of beyond 5G (B5G) cellular communication systems. Nevertheless, obstacles such as constrained resources and imperfect CSI continue to present challenges, prompting the search for novel solutions aimed at bolstering both user capacities and overall SC. This research paper presents a novel methodology called MISO-NOMA-HBF-BFNN, which leverages the integration of NOMA, HBF, and DL-based BFNN to effectively tackle the aforementioned obstacles. Our proposal suggests combining NOMA with MISO-HBF to enable multiuser access. Additionally, we aim to improve performance by optimizing analog precoders for CEUs using DL-based BFNN. The subsequent sections will provide a comprehensive explanation of the approach and execution of the proposed MISO-NOMA-HBF-BFNN scheme, encompassing the simulation configuration and assessment criteria. The efficiency of the proposed scheme is compared and evaluated with existing schemes (e.g., MISO-NOMA-HBF and MISO-OMA-HBF-BFNN) and demonstrated through simulation results, specifically in relation to user capabilities and SC under varied scenarios, including varying pilot-to-noise ratios (PNR) and poor CSI.

2. SYSTEM MODEL

In this scenario, a narrowband downlink DL MISO-NOMA system [14]-[18] which illustrated in Figure 1, with HBF and BFNN is considered in a millimeter-wave (mmWave) communication environment. Let’s break down the key components and their roles in this system:

A. System setup:
- Base station (S): a single base station serves as the source in the system. It is equipped with one radio frequency (RF) chain and multiple transmit antennas (N) antennas.
- Users
- Cell center user (CCU): this user, denoted as (UE_1) is positioned near the base station (S).
- Cell edge user (CEU): this user, denoted as (UE_2) is located near the cell edge, farther away from the base station.

B. Transmission scheme:
- MISO-NOMA: multiple input single output NOMA is employed. It allows multiple users to share the same time-frequency resources by superimposing their signals and decoding them at the receiver.
- Hybrid beamforming (HBF)
- Digital precoder ($\mathrm{v_D}$): a scalar digital precoder applied to the superimposed signal. This precoder manipulates the signal in the digital domain before transmission.
- Analog precoder ($\mathrm{v_{RF}}$): an ($\mathrm{N} \times 1$) analog precoder combined with phase shifters. This precoder manipulates the signal in the analog domain before transmission through the (N) transmit antennas.
- Superimposed signal (A): this signal is simultaneously transmitted towards both users, composed of data symbols for ($\mathrm{UE_1}$) ($\mathrm{x_1}$)and ($\mathrm{UE_2}$) ($\mathrm{x_2}$) weighted by power allocation coefficients $\mathrm{p_1}$ and $\mathrm{p_2}$ respectively, where $\mathrm{p_1} + \mathrm{p_2} = 1$ and $\mathrm{p_1} < \mathrm{p_2}$.

C. Signal representation:
- The superimposed signal (A) can be mathematically represented as:

$$A = (\sqrt{p_1 P} x_1 + \sqrt{p_2 P} x_2)$$

where P is the total transmitted power from the base station;
$\mathrm{x_1}$ and x_2 are the data symbols, p_1 and p_2 represent the power allocation for UE_1 and UE_2 respectively

D. Spatial consideration:

- Distances d_1 and d_2: these represent the distances of (UE_1) and (UE_2) from the base station (S) respectively. Typically, $(d_1 < d_2)$ due to the positioning of (UE_1) and (UE_2) within the cell.
- The CEU is situated near the cell edge, is marked as UE_2 in Figure 1. The precoded and superimposed signal $(A = \sqrt{p_1 P}x_1 + \sqrt{p_2 P}x_2)$ can be represented by (1):

$$\chi = v_{RF}\, v_D A \tag{1}$$

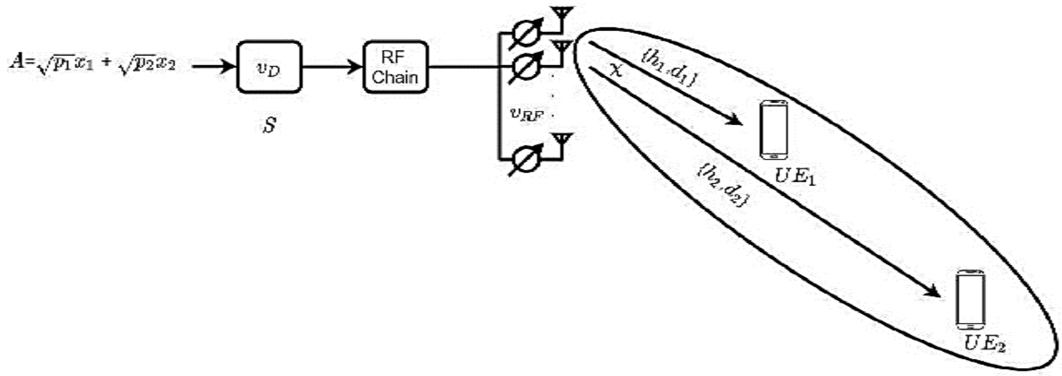


Figure 1. System model of proposed MISO-NOMA-HBF-BFNN scheme

In summary, the system employs HBF with digital and analog precoders to manipulate the transmitted signal, allowing for efficient transmission to multiple users simultaneously. The MISO-NOMA scheme enables multiple users to share the same resources, with power allocation coefficients determining the contribution of each user to the superimposed signal. Finally, the spatial positioning of users within the cell is taken into account to optimize signal transmission based on their distances from the base station.

Again, in the described system architecture shows in Figure 2, a narrow band downlink DL MISO-NOMA-HBF-BFNN scheme is implemented in a mmWave communication system. Let's break down the elaboration of various components and processes involved:

E. Channel model:

- The channel response between the base station (S) and the users $(UE_1$ and $UE_2)$ is modeled using a Saleh-Valenzuela mmWave channel model. This model incorporates a combination of line-of-sight (LOS) and non-line-of-sight (NLOS) paths.
- The channel response (h_k^H) is represented as a sum of complex gains (α_l) multiplied by antenna array response vectors $\left(a_l^H(\phi_t^l)\right)$ at the base station. The channel response can be represented by (2) [12]-[14]:

$$h_k^H = \sqrt{\frac{N}{L}} \sum_{l=1}^{L} \alpha_{k_l} a_l^H(\phi_t^l) \tag{2}$$

where α_l is the complex gain of the l^{th} path and $a_t(\phi_t^l)$ represents the antenna array response vector at S, with (ϕ_t^l) representing the departure azimuth angle related to the path l. $l = 1$ represents a LOS component in h_k^H.

F. Received signal at users:

- The received signal at UE_1 and UE_2 $(y_1$ and $y_2)$ is obtained by multiplying the transmitted superimposed signal (A) with the channel response and the analog and digital precoders $(v_{RF}$ and $v_D)$. The received signal at UE_1 and UE_2 can be expressed by (3) and (4):

$$y_1 = h_1^H v_{RF} v_D A + n_1 \tag{3}$$

$$y_2 = h_2^H v_{RF} v_D A + n_2 \tag{4}$$

- Additive complex Gaussian noise (n_k) is added to the received signals, characterized by zero mean and covariance σ_k^2.

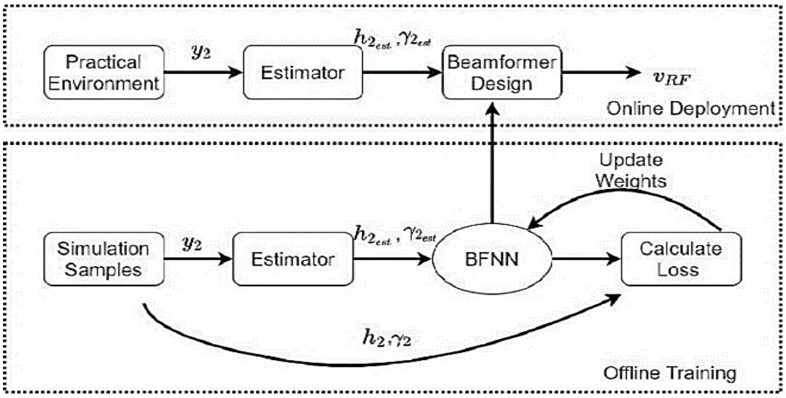


Figure 2. Principle of BFNN based MISO-NOMA-HBF for CEU

G. BFNN design for UE_2:

- Due to the higher path loss between S and UE_2, a unique BFNN technique is devised to optimize the analog beamforming for the S and UE_2 link.
- The BFNN is trained to predict the optimized analog beamforming vector (v_{RF}) based on estimated channel parameters $\left(h_{2_{est}}\right)$ and SINR estimation ($\gamma_{2_{est}}$).
- A self-defined lambda layer is included at the end of the BFNN to enforce a 'sigmoid' activation function on the output, ensuring it falls within the range (0,1). This is crucial as analog beamforming involves phase shifters, and the phase values must be within a specific range.

  Therefore, the complex output value can be expressed by (5):

$$v_{RF} = e^{j.2\pi\alpha_2} = \cos(2\pi\alpha_2) + j.sin(2\pi\alpha_2) \quad (5)$$

  Because of the 'sigmoid' activation function, α_2 symbolizes the real input value [13] within the range (0,1) where $j = \sqrt{-1}$, $2\pi\alpha_2$ is corresponding to phases of v_{RF} .
- The loss function of the BFNN is derived to minimize the SINR and maximize the channel capacity at UE_2. The loss function due to the considered BFNN can be derived as follows [13]:

$$Loss = \frac{1}{M}\sum_{m=1}^{M} \log_2 (1 + \frac{\gamma_{2m}}{N}||h_{2_m}^H v_{RF,m}||^2 \quad (6)$$

  where M represents the total number of samples for training, and γ_{2_m}, h_{2_m}, and $v_{RF,m}$ represent the SINR, CSI, and output analog BF (v_{RF}) associated with the m^{th} sample, respectively. The loss reduction is related to the increase of the average channel capacity of the UE_2 [13].

H. BFNN training and deployment:

- The BFNN is trained offline using randomly generated channel samples and SINR values. The loss is calculated based on the predicted analog beamforming vectors and the actual SINR values.
- During online deployment, practical mmWave channel estimation techniques are used to estimate the channel parameters at UE_2. These estimated parameters are fed into the trained BFNN to generate optimized analog beamforming vectors.

I. BFNN structure:

- The BFNN structure consists of multiple dense layers with ReLU and sigmoid activation functions. The dense layers of the BFNN were set to 256, 128, and 64 neurons, accordingly [13] which is shown in Table 1.

Table 1. Parameters of BFNN for CEU

Layer name	Function	No. of Params.	O/P Dim.
Input layer	\	0	129 × 1
Dense layer 1	reLu	33024	256 × 1
Dense layer 2	reLu	32896	128 × 1
Dense layer 3	sigmoid	8256	64 × 1
Lambda layer	\	0	64 × 1

– Batch normalization layers are incorporated for convergence.
– The input to the BFNN includes the real and imaginary parts of the estimated channel parameters $(h_{2_{est}})$, concatenated with SINR estimation $(\gamma_{2_{est}})$.
– The output of the BFNN undergoes a modulus operation using the lambda layer to obtain the final analog beamforming vector.

J. Training dataset:
– The training, testing, and validation datasets contain a large number of samples to ensure the robustness and generalization of the BFNN.
– Training data includes various channel conditions and SINR levels to cover a wide range of scenarios. In this study, the training, testing, and validation sets contained 10^5, 10^4, and 10^4 samples, respectively [13].

Overall, the described BFNN-based optimization technique for analog beamforming in the MISO-NOMA-HBF system aims to enhance the performance of the mmWave communication system by efficiently allocating resources and mitigating the effects of channel variations.

3. CHANNEL CAPACITY

3.1. Capacity of MISO-NOMA-HBF-BFNN

The signal to interference and noise ratio (SINR) of UE_1 and UE_2 are expressed as γ_1 and γ_2 respectively. γ_1 and γ_2 can be expressed as follows for the proposed scheme:

$$\gamma_1 = p_1||h_1^H \boldsymbol{v_{RF}} \boldsymbol{v_D}||^2 \rho \tag{7}$$

$$\gamma_2 = \frac{p_2||h_2^H \boldsymbol{v_{RF}} \boldsymbol{v_D}||^2 \rho}{p_2||h_2^H \boldsymbol{v_{RF}} \boldsymbol{v_D}||^2 \rho + 1} \tag{8}$$

where $\rho = \frac{P}{\sigma^2}$ is the transmit signal-to-noise ratio (SNR). The channel capacity of UE_1 is expressed as C_1 and the channel capacity of UE_2 can be expressed as C_2**.** The user channel capacities can be expressed by (9) and (10).

$$C_1 = log_2(1 + \gamma_1) \tag{9}$$

$$C_2 = log_2(1 + \gamma_2) \tag{10}$$

The optimal value of v_D for maximizing C_2 is represented by $\sqrt{\frac{p_2}{N}}$. Afterwards, the HBF optimization problem for v_{RF} for UE_2 can be expressed as follows [13]:

$$\min_{v_{RF}} \ \log_2\left(1 + \frac{p_2||h_2^H \boldsymbol{v_{RF}} \boldsymbol{v_D}||^2 \frac{\rho}{N}}{p_2||h_2^H \boldsymbol{v_{RF}} \boldsymbol{v_D}||^2 \frac{\rho}{N} + 1}\right) \tag{11}$$

subjected to $[v_{RF}]_i|^2 = 1$ and $i = 1, \dots, N$ [13]. In this study $\gamma_{2_{est}} = \gamma_2$ is assumed because the SINR can be estimated more accurately than the CSI. Where, $\gamma_{2_{est}}$ is the estimated SINR [13]. Furthermore, the SC (C_S) of the proposed MISO-MISO-NOMA-HBF-BFNN can be derived by adding C_1 and C_2 as in the (12):

$$C_S = C_1 + C_2 \tag{12}$$

3.2. Capacity of MISO-OMA-HBF-BFNN

The MISO-OMA-HBF-BFNN scheme employs time-division multiple access (TDMA) to allocate independent time slots for transmitting individual symbols to UE_1 and UE_2. These time slots, denoted as t_1 and t_2, are divided equally ($t_1 = t_2 = \frac{1}{2}$) to compare user channel capacities and the SC. The total transmit power from S is represented by P [13], [16]. Thus, the achievable capacity of UE_1, UE_2, and the SC can be presented as follows for the MISO-OMA-HBF-BFNN scheme:

$$C_1^{OMA} = \frac{1}{2} log_2(1 + \gamma_1^{OMA}) \tag{13}$$

$$C_2^{OMA} = \frac{1}{2} log_2(1 + \gamma_2^{OMA}) \tag{14}$$

where $\gamma_1^{OMA} = ||h_1^H v_{RF} v_D||^2 \rho,\ \gamma_2^{OMA} = ||h_2^H v_{RF} v_D||^2 \rho$. Moreover, the optimal v_D for enhancing C_2 is expressed by $\sqrt{\frac{\rho}{N}}$. Then, the optimization problem for v_{RF} due to MISO-OMA-HBF-BFNN for UE_1 and UE_2 can be expressed as follows by [13].

$$\min_{v_{RF}} \quad \log_2 (1 + ||h_1^H v_{RF}||^2 \frac{\rho}{N}) \tag{15}$$

$$\min_{v_{RF}} \quad \log_2 (1 + ||h_2^H v_{RF}||^2 \frac{\rho}{N}) \tag{16}$$

Subject to $[v_{RF}]_i|^2 = 1$ and $i = 1, \ldots, N$. As the SINR can be estimated more accurately than the CSI, hence $\gamma_{1_{est}}^{OMA} = \gamma_1^{OMA}$ and $\gamma_{2_{est}}^{OMA} = \gamma_2^{OMA}$ are assumed in this study. Where $\gamma_{1_{est}}^{OMA}$ and $\gamma_{2_{est}}^{OMA}$ are the estimated SINR [13]. Furthermore, the SC of MISO-OMA-HBF-BFNN can be derived by adding C_1^{OMA} and C_2^{OMA} as in the (17).

$$C_S^{OMA} = C_1^{OMA} + C_2^{OMA} \tag{17}$$

4. RESULTS AND DISCUSSION

In the simulation setup described, several key parameters and techniques are employed to evaluate the performance of the proposed MISO-NOMA-HBF-BFNN scheme and compare it with existing schemes under various conditions. Let's delve into the elaboration of the simulation results and comparisons:

A. Simulation parameters

A MISO-based array antenna with $N = 64$ elements and uniform linear half-wave spacing is considered at the base station (S). The Saleh-Valenzuela-based mmWave channel model is utilized for all communication links [19]. Parameters such as [20] power allocation (p_1 and p_2), total transmitted power (P), and number of channel paths (L) are set according to the defined system model. Parameters $p_1 = 0.2$, $p_2 = 1 - p_1$, $P = 1$ and $L = 3$ were considered in this study. The PNR is chosen as an indicator of [21], [22] channel estimation due to practical considerations where PNR may differ from SNR.

B. BFNN parameters and optimization

The BFNN parameters are defined [23], [24] according to Table 1, and they remain constant throughout all experiments. The Adam optimizer with a learning rate initialized at 0.001 is employed for training the BFNN. The training samples cover a wide range of SNR values (-20 dB to 20 dB), and imperfect CSI is considered for all comparisons.

C. Simulation findings

- Figure 3 depicts capacity comparisons for a PNR of 20 dB and estimated channel paths (L_{est}) equal to 3.
- The proposed MISO-NOMA-HBF-BFNN scheme outperforms other schemes significantly in terms of user capacities. This improvement is attributed to the optimized analog beamformer v_{RF} based on estimated channel parameters and SINR. Both the CCU and CEU capacities are notably enhanced compared to other schemes, resulting in improved spectral efficiency (SC).
- Figure 4 shows the capacity and SC caoparison for both PNR and L_{est} optimized values.
- Hence, Figure 4(a) illustrates CCU capacity comparisons under a lower PNR of 0 dB and $L_{est} = 3$.
- The proposed scheme continues to exhibit superior performance, providing higher user capacities compared to existing schemes even under lower PNR conditions. Although capacities decrease compared to the higher PNR scenario, the proposed scheme maintains its advantage due to the effectiveness of the BFNN-based optimization technique.
- Figure 4(b) shows channel capacity comparisons for a PNR of 20 dB and $L_{est} = 1$.
- The proposed scheme demonstrates significantly higher user channel capacities and SC compared to conventional schemes under lower SNR conditions [25]. However, capacities degrade compared to conventional schemes under higher SNR conditions due to less effective optimization of the analog beamformer v_{RF} in the presence of less accurate channel path estimation (L_{est}). The results highlight the effectiveness of the proposed BFNN-based optimization technique in improving system performance under various channel conditions.
- The scheme exhibits resilience to lower PNR and less accurate channel estimation, showcasing its potential for practical deployment in mmWave systems. However, under high SNR conditions, the scheme's performance may be impacted by the accuracy of channel path estimation, necessitating further investigation into robust estimation techniques.

In summary, the simulation results underscore the efficacy of the proposed MISO-NOMA-HBF-BFNN scheme in enhancing user capacities and spectral efficiency in mmWave communication systems, particularly under challenging channel conditions.

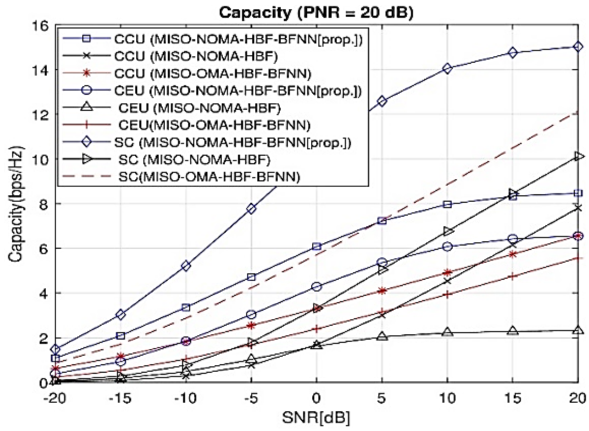
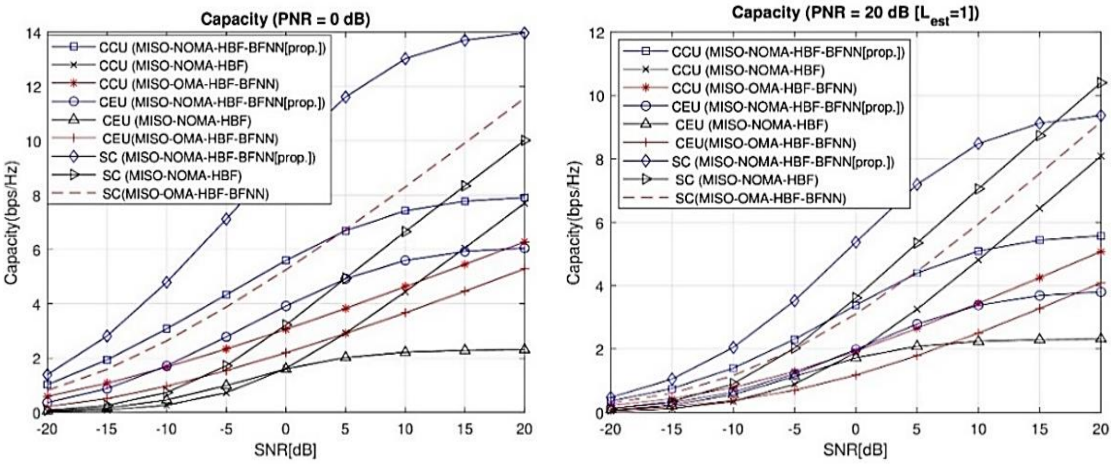


Figure 3. Capacity comparisons for PNR = 20 dB and $L_{est} = 3$



(a) (b)

Figure 4. Capacity and SC comparisons for PNR and L_{est} (a) Capacity comparisons for PNR = 0 dB and $L_{est} = 3$ and (b) SC comparisons for PNR = 20 dB and $L_{est} = 1$

5. CONCLUSION

The MISO-NOMA-HBF-BFNN scheme is proposed in this study for mmWave-based downlink MISO-NOMA B5G cellular communication. The MISO-NOMA-HBF-BFNN scheme's efficacy is thoroughly examined in terms of SC and user channel capacities. Additionally, the user channel capacities and SC of the proposed scheme are compared to the conventional MISO-NOMA-HBF and MISO-OMA-HBF-BFNN schemes. The analysis of the results demonstrates that the proposed scheme enhances the CCU channel capacity, CEU channel capacity, and SC in comparison to the other compared schemes. This improvement is attributed to the BFNN for CEU, which is a consequence of imperfect CSI. This is because the imprecise CSI allows the BFNN to effectively optimize the analog beamformer for CEU. Consequently, the user channel capacities and SC of the proposed MISO-NOMA-HBF-BFNN scheme are enhanced in comparison to other existing schemes. The proposed scheme is also compared to other existing schemes, and the impact of various PNR and L_{est} is also analyzed. The result analysis also demonstrated that the proposed scheme outperforms other existing schemes in terms of user capacities and SC for various PNR and L_{est} as well.

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