Random Forest Regression-Based Power Allocation for Sub-Connected Hybrid Beamforming-NOMA Systems

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***Abstract*—We solve the sum rate approximation problem in downlink millimeter-wave (mmWave) non-orthogonal multiple access (NOMA) systems under hybrid beamforming with sub-connected architecture. A unique data-driven power allocation scheme based on random forest regression (RFR) is proposed, where historical link datasets generated using distance- and path-loss model-based dynamic power allocation schemes serve as training inputs. The RFR scheme predicts power coefficients that balance user fairness and system throughput. Simulation results validate that the RFR scheme achieves performance close to model-based baselines while substantially lowering computation complexity, offering a scalable and practical solution for future mmWave-NOMA networks.**

***Index Terms*—Data rate, hybrid beamforming, non-orthogonal multiple access, mmWave, random forest regression, sum rate.**

I. Introduction

THE quest for high data rate service in 6G can be satisfied by exploring untapped millimeter Wave (mmWave) spectrum. However, mmWave propagation signals suffer from pathloss, penetration loss, and even shadowing in both line of sight (LOS) and non line of sight (NLOS) [1]. Antenna beamforming has been identified as a feasible solution to mitigate these propagation effects [2]. Consequently, the current fully digital beamforming (FDBF) will consume substantial power for massive multiple input multiple output (MIMO) system, because each antenna is dedicated to a single transceiver's RF chain [3]. Hybrid beamforming (HBF) has been recommended as a practical substitute to a FDBF in order to reduce hardware complexity, which in turns diminishes the considerable power consumption and implementation cost. In particular, the impact of mmWave propagation losses on 6G power consumption has been quantitatively analyzed in [1], where energy efficiency gaps were detailed in Figs. 6 and 7 for different HBF schemes.

Incorporating non-orthogonal multiple access (NOMA) with the standard multiuser MIMO will further improve the system spectrum efficiency [4]. Concerted efforts have been made among researchers to solve users' power ration coefficient optimization problem in power domain NOMA, which involves a superposition of users' symbols with different power levels at the base station (BS) to achieve multiple access. HBF-NOMA optimization problems are regarded as non-convex and hard to solve. Therefore, the problem is usually simplified exploiting a round robin approach for optimzing HBF precoders and power allocation factors. In literature, power-domain NOMA configurations such as fixed power (FP) and dynamic power (DP) approaches have been investigated [5], [6]. The DP proposed in [6] was based on an iterative search, which enabled it to result in a substantially high overhead. Ideas in [5], [7] have allocated fixed user's power in a greedy manner and the users' fairness may not be met especially under the users' channels being dynamic and the cluster users being more than two.

Recently, successive interference cancellation (SIC) based dynamic power allocation (DPA) approach has been introduced to dynamically allocate power to more than two users per cluster [8]. Searching for optimized power allocation factors under the joint constraints of both SIC and unity summation of total power factor leads to high overhead as the number of cluster users increases. A model-based DPA approach recently introduced in [1] may greedily select power factors that maximize sum rate, which may be unfair to the weak user's access. Furthermore, the model-based DPA approach may be suboptimal to iterative method but less complicated under the assumption that an SIC can be successively processed at the strong user if the users' ordering is based on the effective hybrid (digital-analog) channel weights of each cluster user in a descending order [5].

Unlike DPA methods that rely on either greedy model-based heuristics or iterative search algorithms, we introduce that random forest regression (RFR) [9] scheme learns from historical distance and inverse pathloss (IPL)-based data (or models) to predict fair and effective power coefficients in a non-iterative, computationally efficient way without compromising sum rate maximization in both LOS and NLOS scenarios of a mmWave urban microcell (UMi) environment. Compared to reinforcement learning (RL), which often requires online interaction, convergence tuning, and large state-action exploration, the proposed non-iterative RFR scheme is trained offline exploiting labeled data derived from sum rate simulations, allowing for faster and more stable deployment, rendering it applicable to near real-time optimization tasks within the 6G radio acceas networks.

II. Methodology

The RFR powering scheme visualized in Fig. 1 is proposed for a downlink HBF-NOMA network illustrated in Fig. 2 to optimize the power allocation coefficients. Readers are referred to Section II in [8] for detailed descriptions of the HBF-NOMA system models and structures. The RFR powering scheme's framework consists of the HBF-NOMA system's environment and the RFR-based power factor optimization training agent at the BS. HBF-NOMA environment at the lower part is assumed to have the knowledge of network parameters, namely received signal to interference plus noise ratio (SINR) denoted as $\mathbf{G} \in \mathbb{C}^{N\times M}$ having an element $g_{(n,m)}$ for each user, DPA power factors $\mathbf{A}^{z} \in \mathbb{R}^{N\times M}$, and $\mathbf{A}^{\psi} \in \mathbb{R}^{N\times M}$ computed based on distance and IPL model expressed as (40) and (41) in [1] having each user's power factor element $\alpha^{z}_{(n,m)}$ and $\alpha^{\psi}_{(n,m)}$, respectively, UMi link pathloss factor matrix is also symbolized as $\mathbf{C} \in \mathbb{R}^{N\times M}$ having each user's $c_{(n,m)}$ pathloss factor, and finally users' distance to BS matrix $\mathbf{Z} \in \mathbb{R}^{N\times M}$, which constitutes each user's distance $z_{(n,m)}$. Notably, N and M as well as $\mathbb{C}$ and $\mathbb{R}$ represent the maximum number of clusters and users in the NOMA network as well as the sets of complex and real numbers, respectively.

The RFR (power) optimization module at the upper part contains two elements, namely the first one computes the users' data rates and network's sum rate dataset arisen from the successive deployment of both power ration factors based on the distance and IPL model functions at the BS as well as the second one intelligently predicts optimized $\mathbf{A}^{\rho} \in \mathbb{R}^{N\times M}$ users' power ration coefficients capable of offering fair access to users' data rate. Explicitly, in Fig. 1, the lower part of RFR optimization module (green) processes a user's data rate on the basis of each power ration factor's model and the observed user's received SINR from the HBF-NOMA environment. Then, at the upper part of RFR optimization module (yellow), the associated sum rate and data rate dataset is deployed for RFR training for the purpose of predicting a fair access power factor $\mathbf{A}^{\rho}$ for HBF-NOMA deployment. Details of the proposed powering scheme leveraging the RFR training agent are presented under Subsection II-B.

Although the proposed RFR-based powering scheme can be deployed for both (fully connected and sub-connected) structure HBF-NOMA systems, and can utilize numerically iterative-based powering scheme's dataset for better training and prediction, throughout this paper, the analysis and simulation are limited only to a single stream sub-connected

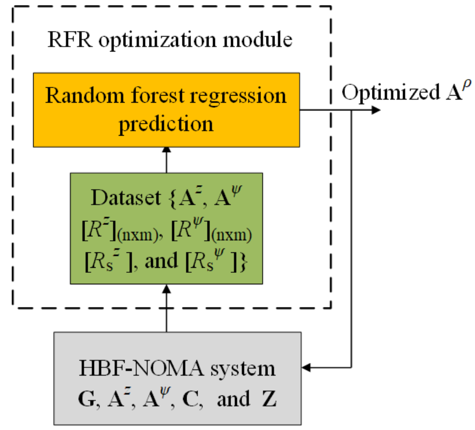


Fig. 1: Random forest regression power allocation framework for HBF-NOMA system (refer to Fig. 2 for the brief illustration of a typical SCS-HBF-NOMA system's environment).

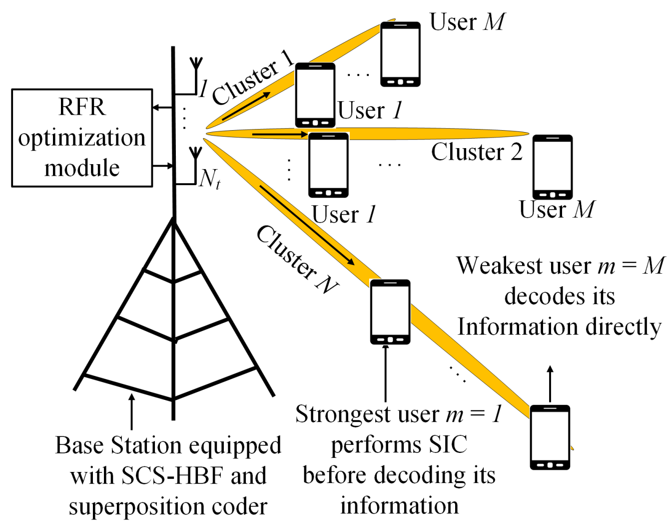


Fig. 2: The proposed down link mmWave HBF-NOMA system equipped with a SCS-HBF precoder at the BS to beamform NOMA signals to M single antena users in each cluster (refer to Fig. 1 in [8] for detailed descriptions of the HBF-NOMA system models and structures).

structure (SCS) version of HBF-NOMA, which offers more energy efficiency compared to the fully connected structure (FCS) HBF-NOMA [8]. The simulation environment constitutes SCS-HBF-NOMA having an N_t antennas aided BS with $N \cdot M$ clustered users. Each of the NOMA users is equipped with a single antenna. BS and each user are equipped with N and a single RF chains, respectively. HBF-NOMA channel is based on NYU mmW channel model [10].

It is assumed that the single carrier channel coefficient $\mathbf{h}_{(n,m)} = \sum_{v=1}^{V} \gamma_{(n,m,v)} e^{j\Phi_{(n,m,v)}} e^{-j2\pi f \tau_{(n,m,v)}} \mathbf{a}_t(\phi_{(n,m,v)})$, where $\gamma_{(n,m,v)}$, $\Phi_{(n,m,v)}$, f, $\tau_{(n,m,v)}$, and $\mathbf{a}_t(\cdot)$ denote amplitude of the channel gain in the vth resolvable LOS or NLOS multipath link component, the phase of the multipath component, carrier frequency, time delay, and array steering function depending on angle of departure (AOD) ϕ at the BS, respectively. The NYUSIM software is set up for both LOS and NLOS scenarios, exploiting the information in Table I to create DirPDPinfo.mat for the $\mathbf{h}_{(n,m)} \in \mathbb{C}^{1\times N_t}$ simulation that takes advantage of the NYU channel model. According to their channel magnitudes, users in the same angle of arrival (AOA) θ are grouped together and arranged as follows: $|\mathbf{h}_{(n,1)}\mathbf{F}\mathbf{d}_n| > |\mathbf{h}_{(n,2)}\mathbf{F}\mathbf{d}_n| > \cdots > |\mathbf{h}_{(n,M)}\mathbf{F}\mathbf{d}_n|$, where $\mathbf{F}$ and $\mathbf{d}_n$ denote analog beamforming matrix and nth cluster users' digital precoding vector, respectively.

The users' symbols are superimposed at the BS employing the DPA power allocation factor prior to transmission, that is $s_n = \sum_{m=1}^{M} \sqrt{\alpha_{(n,m)} \times p_n} \times s_{(n,m)}$, where $\alpha_{(n,m)}$, $s_{(n,m)}$, and $p_n = \frac{P}{N}$ represent the power ration coefficient, transmitted symbol of a user $U_{(n,m)}$, and nth cluster power, respectively. Before the strongest user detects its own symbol, SIC is applied to the symbols of the other weak users. Therefore, $(M-1)$ SIC processings are performed before the weakest users finally detect its own symbols. This SIC is attainable because strong user rates are higher than weak user rates. Our previous work in [1] presented multistream per user with model-based DPA for HBF-NOMA system. Dataset derived from its simulation can directly be leveraged to train the proposed RFR scheme, extending its applicability to more complex scenarios with more than two users per cluster. To align with energy-efficient application contexts such as low-power 6G IoTs or vehicular networks, we limit further analysis in this paper to $M = 2$ users per cluster. Hence, the SIC decoding order follows $R_{(n,1)} \geq R_{(n,2)\to(n,1)}$ constraint, where $R_{(n,2)\to(n,1)}$ is the rate received at $U_{(n,1)}$ after decoding the message of $U_{(n,2)}$. Details on SIC decoding orders are referred to Section II (Page 1335, Paragraph 1) in [8].

Therefore, attainable rate of the user $U_{(n,m)}$ is formulated as:

$$R_{(n,m)} = \log_2(1 + g_{(n,m)}), \tag{1}$$

where $g_{(n,1)}$ and $g_{(n,2)}$ of strong and weak users are formulated as $\zeta_{(n,1)}|\mathbf{h}_{(n,1)}\mathbf{F}\mathbf{d}_n|^2$ and $\frac{\zeta_{(n,2)}|\mathbf{h}_{(n,2)}\mathbf{F}\mathbf{d}_n|^2}{\beta^{intra}_{(n,2)}+\beta^{inter}_{(n,2)}+1}$, respectively. $\zeta_{(n,m)} = \frac{p_n \times \alpha_{(n,m)}}{\sigma^2_{(n,m)}}$ denotes signal to noise (SNR) power for user $U_{(n,m)}$ and $\beta^{intra}_{(n,2)} = \zeta_{(n,1)}|\mathbf{h}_{(n,2)}\mathbf{F}\mathbf{d}_n|^2$ indicates the intra-cluster interference at the $U_{(n,2)}$ after SIC processing at the strong user $U_{(n,1)}$. Moreover, the inter-cluster interference $\beta^{inter}_{(n,2)}$ represents $\sum_{l\neq n}^{N}\sum_{q=1}^{2}\zeta_{(l,q)}|\mathbf{h}_{(n,2)}\mathbf{F}\mathbf{d}_l|^2$ at the $U_{(n,2)}$ in the nth cluster. Also, $\mathbf{F}$, $\mathbf{d}$, and $\sigma^2_{(n,m)}$ symbolize analog beamforming matrix, digital beamforming vector, and noise variance of additive white Gaussian noise arising from the user $U_{(n,m)}$ antenna, respectively. Hence, we formulate the sum rate performance of the mmWave power-domain NOMA system as

$$R_s = \sum_{n=1}^{N}\sum_{m=1}^{M} R_{(n,m)}. \tag{2}$$

A. Sum Rate Approximation Problem

The sum rate approximation problem indicates that the sum rate loss arising from implementing a fair data rate access powering scheme for HBF-NOMA communication should be minimal. This can be mathematically expressed for HBF-NOMA as the maximization of the sum rate in (2), while adhering to the related constraints outlined in (3b) to (3e), mathematically

$$\underset{\{\mathbf{F},\mathbf{D},\boldsymbol{\alpha}\}}{\text{maximize}} \quad R_s \tag{3a}$$
$$\text{subject to} \quad |\mathbf{F}(i,j)|^2 = \mathcal{M}_t^{-1}, \tag{3b}$$
$$\|\text{blk. diag}[\mathbf{F}]\cdot\mathbf{D}\|_F^2 = N, \tag{3c}$$
$$R_s^z \simeq R_s^\psi \simeq \hat{R}_s, \tag{3d}$$
$$\sum_{m=1}^{2}\alpha_{(n,m)} \leq 1, \quad \alpha_{(n,m)} > 0, \tag{3e}$$

where $\mathbf{D} \in \mathbb{C}^{N\times N}$, $\mathcal{M}_t$, $\hat{R}_s$, R_s^z, R_s^ψ, and blk. diag. denote the digital precoder, the number of antenna elements for each sub array at the transmitter, sum rate achieved by RFR, distance, IPL-based power ration prediction schemes, and SCS's block diagonalization constraint, respectively. Constraints in (3b) and (3c) ensure a unit magnitude element in analog precoder and power consumed by hybrid precoder constrained to N are achievable, respectively. (3d) denotes sum rate approximation problem. Finally, (3e) represents constraints of power factors of users.

B. Proposed Solution

Maximization of (3a) is non-convex as it involves a joint optimization of both the HBF precoder and users' power factor optimization problems. Therefore, the optimization problem solution is simplified exploiting a round robin approach between the HBF design optimization and power coefficient optimization. We adopt the Phased Zero Forcing (P-ZF) approach in [8] to optimize HBF precoder, while optimization of powers for users is solved by the proposed RFR scheme for typical UMi links. To elaborate it a little bit further, we practically formulate two DPA models, based on user's distance and inverse pathloss denoted as DPA-D and DPA-IPL to optimize users' power coefficients using (40) and (41) in [1], respectively. Furthermore, each model ensures that a summation of the clustered user power allocation factors is restricted to unity, and power allocation factors are dynamically allocated to satisfy $\alpha_{(n,1)} < \alpha_{(n,2)}$. The sum rate approximation problem is solved using the proposed RFR powering scheme.

A typical UMi links can either be LOS or NLOS. HBF-NOMA powers practically formulated are tested for each of the UMi links to determine their corresponding data rate and sum rate. Results obtained guide us to produce an RFR scheme's dataset deployed for RFR training (yellow) prediction. Meanwhile, deployed DPA-D and DPA-IPL coefficients for HBF-NOMA operation may not offer the users' fair access due to the exponent of z parameter, which tends to favour strong users to maximize sum rate. In order to obtain a fair access power factors, a RFR training prediction scheme is employed to solve regression problems associated with the available dataset exploiting the average value approach at the decision tree leaf node [9]. Finally, the predicted fair access $\alpha^\rho_{(n,m)}$ is returned to update optimized $\mathbf{A}^\rho$ for HBF-NOMA deployment. RFR prediction processing is therefore presented in II-C for more clarification.

C. Random Forest Regression prediction

The training dataset[1] was constructed by simulating link-level transmissions over a SNR range spanning from -10 dB to 30 dB in increments of 5 dB, leading to a total of 9 discrete SNR levels. A total of $T(=18)$ training samples were generated in MATLAB for each of the LOS and NLOS scenarios exploiting the NYUSIM channel simulator, with channel parameters detailed in Table I. Each sample includes link type (0 and 1 decode LOS and NLOS links, respectively), model j (0 and 1 decode distance and IPL models, respectively), $\alpha_{(i,j)}$, ${}_{i\&j=1,2}$, SNR, $R_{(i,j)}$, ${}_{i\&j=1,2}$, and R_s. Therefore, the training data can the be modeled as $\mathcal{D}_{\text{train}} = \{(\mathbf{X}_i)\}_{i=1}^{T}$. These features enable the RFR model to learn from the regression patterns between the sum rates corresponding to each model-based power coefficient indexed by $j(=1,...,M_T)$. The fairness-optimal power coefficient is then predicted as the average value along the segment of the regression curve where the minimum predicted sum rate begins to increase and the maximum predicted value starts to saturate.

The RFR model is an ensemble of M_T decision trees. Each tree is trained on a bootstrapped subset of the training data. For a given input $\mathbf{X}$, the prediction of the j-th tree is $\hat{\mathbf{A}}_j^{\rho}$, and the ensemble prediction of the RFR model is given by:

$$\hat{\mathbf{A}}^{\rho} = \frac{1}{M_T}\sum_{j=1}^{M_T}\hat{\mathbf{A}}_j^{\rho}, \tag{4}$$

where M_T is the total number of trees in the ensemble. Specifically, the data is partition into training and testing sets using 80 ratio 20, and the RFR model is trained exploiting Scikit-learn, which minimizes the mean squared error internally without requiring a manually defined loss function. During its inference, predicted sum rates having two models-based power coefficients are used to predict optimize power factors across a dense grid of candidate power factors. The optimal factor is then selected by evaluating a fairness-aware criterion that balances rate gains between paired users, exploiting (4).

The RFR-based powering scheme offers a much lower complexity compared to model-based DAP-D and DAP-IPL methods that offer complexity of $\mathcal{O}(MN)$. Specifically, the training complexity of RFR is $\mathcal{O}(M_T \cdot T \cdot d \cdot \log T)$, where d is the feature dimensionality, Once trained, the RFR model performs prediction with constant time inference complexity $\mathcal{O}(M_T)$, enabling real-time adaptability.

III. Results

LOS and NLOS link level simulations of the proposed P-ZF-SCS-HBF-NOMA based on RFR scenarios are implemented for $M(=2)$ users and $N(=2)$ clusters to benchmark the SCS-HBF-NOMA scenarios based on DPA-D and DPA-IPL schemes. Transmit and receive antennas are configured to

[1]SumRateDataset is accessible on https://ieee-dataport.org/documents /sum-ratedataset.

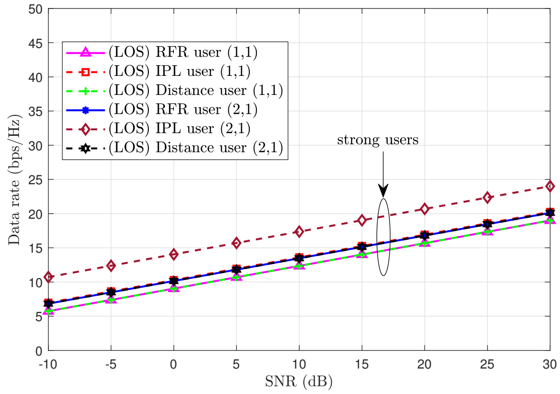
TABLE I: NOMA channel parameters deployed for NYUSIM

Parameters	LOS	NLOS
$z_{(1,1)}$ and $z_{(1,2)}$	42.6, 124.1 $[m]$	83.3, 161.5 $[m]$
$z_{(2,1)}$ and $z_{(2,2)}$	17.8, 177.7 $[m]$	26.3, 195.5 $[m]$
$\phi_{(1,m)}$ and $\phi_{(2,m)}$	20^o, 40^o	20^o, 35^o
$\theta_{(1,m)}$ and $\theta_{(2,m)}$	20^o, 40^o	30, 45^o
BS and users' heights	10 and 1.65 $[m]$	10 and 1.65 $[m]$

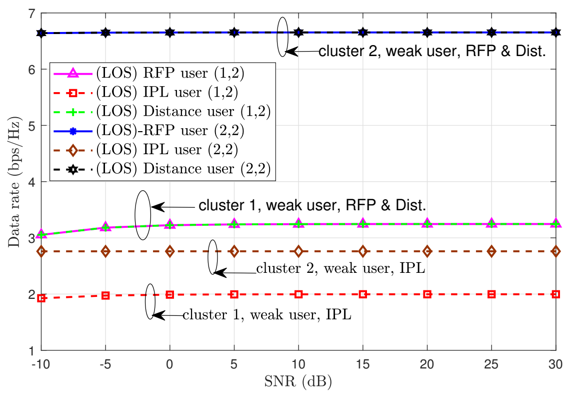
128 and 1, respectively. Pathloss factors $\mathbf{C}$ for Users $U_{(1,1)}$, $U_{(1,2)}$, $U_{(2,1)}$, and $U_{(2,2)}$ are set to $(2.5, 2.4, 2.2, 1.9)$ and $(3.0, 3.0, 3.3, 3.3)$ for LOS and NLOS links as retrieved from NYUSIM channel simulation, respectively. User's deterministic distance $z_{(n,m)}$ is set as shown in Table I. Optimized A^z, A^{ψ}, and A^{ρ} factors matrices for DPA-D, DPA-IPL, and RFR schemes result in [0.1050, 0.8946; 0.0099, 0.9901], [0.2510, 0.7494; 0.1475, 0.8525], and [0.18, 0.82; 0.09, 0.91] for LOS link as well as [0.2101, 0.7899; 0.0178, 0.9822], [0.2703, 0.7297; 0.0352, 0.9648], and [0.24, 0.76; 0.0275, 0.9725] for NLOS link, respectively. A single run simulation is carried out using the deterministic channel model and system configurations for SNR values ranging from $-10[dB]$ to $30[dB]$. Since the objective function is based on the sum rate approximation problem to achieve users' fairness to data rates, the presentation of the performance measure is more focused on the data rate of the users, revealing the impact of the proposed RFR powering scheme solution on offering fairness to users' data rates [11] [12].

Figs. 3 and 4 manifest the attainable data rates for various single stream SCS-HBF-NOMA schemes in LOS and NLOS links, respectively. For the sake of clarity, the weak and strong users' data rates in LOS and NLOS links are separately presented. Specifically, Fig. 3 reveals that at all SNRs, the proposed RFR and DPA-D schemes compared to the DPA-IPL approach experience an average data rate degradation of 10% for strong user $U_{(1,1)}$ in 1st cluster. Instead, an average data rate gain of 62% for weak user $U_{(1,2)}$ in 1st cluster is obtained. Furthermore, in 2nd cluster, the proposed RFR and DPA-D averagely results in 24% data rate degradation for strong user ($U_{(2,1)}$). However, average data rate gain of 59% for weak user ($U_{(2,2)}$) is also attained. Qualitatively, it can be inferred from results of Fig. 3 that the proposed scheme offers more fair access to weak users to compensate its weak beamforming gain in LOS link.

In NLOS link, the proposed RFR compared with the DPA-IPL in Fig. 4 manifests an average data rate degradation of 2% for strong user $U_{(1,1)}$ at all SNRs. Instead, a data rate gain of 6% for weak user $U_{(1,2)}$ in 1st cluster is obtained. Furthermore, the proposed RFR compared with the DPA-IPL degrades by 8% for strong user $U_{(2,1)}$. However, data rate gain of 17% for weak user $U_{(2,2)}$ in 2nd cluster is achieved. It is also worth noting that the proposed RFR compared with DPA-D experiences an average data rate degradation of 5% for weak user $U_{(1,2)}$. Instead, the data rate of strong user $U_{(1,1)}$ is averagely boosted by 2%. Furthermore, the proposed RFR averagely experiences an average data rate degradation of 3%



(a) Strong users



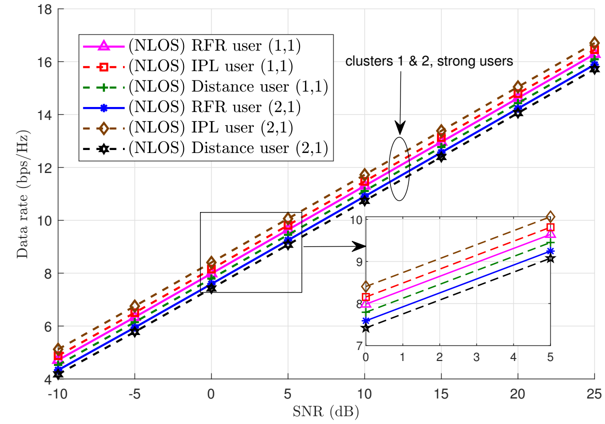
(b) Weak users

Fig. 3: Attainable users' data rates for the proposed single stream P-ZF SCS-HBF-NOMA deploying RFR-based powering approach in LOS link compared with the distance and IPL model based power allocation counterparts.

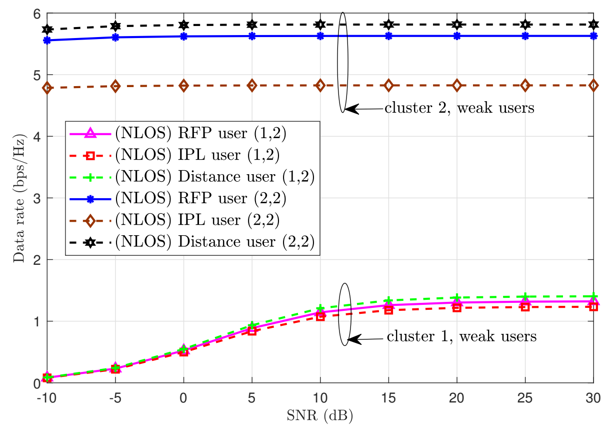
for weak user $U_{(2,2)}$. However, a gain of 2% data rate for strong user $U_{(2,1)}$ is achieved. Hence, it can be deduced from Fig. 4 that the proposed RFR scheme performs better than the DPA-IPL and approaches that of DPA-D method in NLOS link. Qualitatively, the proposed scheme offers fair access to strong users rather than weak users in both clusters so as to maintain the asymptotic sum rate to those of DPA-D and DPA-IPL schemes in NLOS link. The proposed RFR scheme demonstrates a meaningful insight for a feasible candidate having greater potential to offer fair access to various clustered users based on their channel parameters. To verify whether the proposed scheme satisfies the sum rate approximation constraint, the achievable sum rates of the three schemes are also presented in Fig. 5. The results indicate that, despite the proposed scheme providing more equitable access to users, the loss in the sum rate remains negligible in both link scenarios.

IV. Conclusion

In this paper, we have studied a downlink multiuser HBF-NOMA system deployed in a typical UMi environment. We have proposed an RFR-based powering scheme for P-ZF-SCS-HBF-NOMA to address the optimized sum rate approximation



(a) Strong users.



(b) Weak users.

Fig. 4: Attainable users' data rates for the proposed single stream P-ZF SCS-HBF-NOMA deploying RFR-based powering scheme approach in NLOS link compared with the distance and IPL model-based power allocation counterparts.

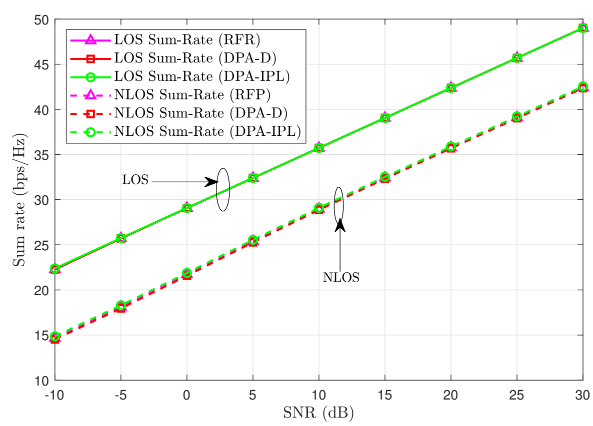


Fig. 5: Achievable sum rate of the RFR power prediction scheme for the HBF-NOMA system, benchmarking the model-based counterparts.

problem. Sum rate dataset associated with both DPA-D and DPA-IPL optimizations were employed for the RFR training to predict an optimized power factor matrix. Because the RFR scheme avoids reliance on complex deep-layer neural networks, the RFR-based approach can generalize across deployment topologies with similar pathloss characteristics, as demonstrated through LOS and NLOS training coverages. The prediction rule leveraged on average value approach of RFR algorithm to predict fairness optimized power factor at the decision tree leaf node. Link level simulation results validated the robustness of our proposed RFR powering scheme for both LOS and NLOS links without jeopardizing users' fair access. Obtained results gave beneficial insight on the realistic performance of the proposed scheme owing to the use of realistic channel model. Therefore, the results can serve as a clear guide for the design stage of a 6G NOMA. Future study will extend the RFR framework to dynamic vehicular scenarios leveraging both online learning and distributed model updates.

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