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A Comparative Analysis of the various Power Allocation Algorithm in NOMA-MIMO Network Using DNN and DLS Algorithm

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Abstract

The high data rate, huge spectrum efficiency, successive interference cancellation (SIC), and ultra-reliable low latency (URLL) are of the demand for next-generation technologies. Non-orthogonal multiple access (NOMA) scheme provides multi-user scaling (multiplexing), optimum spectral efficiency (SE), excellent user-pairing improvement, and a single resource block sharing by multiple users because of which it is a more preferable scheme over orthogonal multiple access (OMA) for the next generation technologies. This article investigates comparative analysis of various power allocation algorithms in multiple-input multiple-output-NOMA (MIMO-NOMA) technology and to come up with the best power allocation algorithm which suited best for MIMO-NOMA technology. Firstly, comparison analysis will be carried out considering direct methodologies followed by power allocation algorithm using Deep Neural Network (DNN) along with the Depth limited search (DLS) algorithm. These techniques are tested on two users initially then followed by multi-user communication. Allocating optimal power to the poor signal strength user terminal (user not receiving appropriate signal power) is a difficult task in actual scenario, and moreover, SIC also creates complexity in the proper allocation of Base station (BS) source power. The above problems can be solved with the assistance of the DNN along with the DLS algorithm, where the weaker user receives maximum power and the stronger user receives minimum power. The DNN-MIMO-NOMA technology, which is based on the DLS algorithm, helps user terminals to get their signals free from noise (inter_user_interference) and with greater precision. The DLS process (algorithm) offers higher potential in MIMO-NOMA with DNN technology for successfully applying SIC. Here, MIMO helps to improve the channel gain. A DLS provides an optimum power allocation (OPA) based on the position of user equipment. The simulation results show that the power allocation method using DNN along with DLS algorithm achieves better performance than the traditional multi-user.

Keywords: Maximum power allocations, MIMO-NOMA, DNN, Successive interference cancellation (SIC), DLS algorithm.

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1. Introduction

NOMA has gained a potential importance in the 5G and beyond technologies because of the various advantages of it over OMA. In NOMA, multiple users are paired simultaneously without any interference from the neighboring user terminals and optimum power allocation (OPA) is also achieved by allocating preferred power levels to the weaker users [1-2]. An internet of things (IoT) demands high throughput and is essential for achieving quality of service [3]. In previous generations, OMA and

OFDM were broadly utilized for wireless communications. Although, with the fast growing demand and vast utilizations, Spectral Efficiency (SE) is unsatisfactory and frame coherence is necessary for OMA and this leads to the need for NOMA [4]. With the NOMA scheme, multiple users share the same time-frequency resources with different power levels. Also, it has become a promising scheme for obtaining better SE in the 5th generation and beyond [5]. NOMA places a greater emphasis on power distribution from the BS to the receivers, tests the interference on the superimposed Signal at the BS and finally SIC happens at the receivers [6]. Hence, it requires an OPA between the BS and the receiver [7]. If OPA is not achieved then SIC may not work properly and cell edge users may not decode its signal perfectly as a result they may receive erroneous signal [8]. Machine learning (ML) is employed for numerous applications in wireless communication systems such as physical secure layer communications, self-network organization and network management. In order to meet the different needs of the future generation wireless communication network Xu.et.al, [9] suggested solutions for assisting the radio in making decisions and adaptive network. Deep learning (DL) technology is used for applications of ML as DL works quite well with huge quantity of information and lower down the model complications [10] & [11]. Some queries relating to the application of ML in the wireless communication network has been structured as mentioned: Why a DNN is an essential component for the wireless communication technology's functioning and design? What is the role of artificial neural networks in future wireless networks? Nowadays, the DNN has become an essential tool for providing features like URLL (latency 1ms), million connections within a square kilometer, 99.9% trust, and vehicle-to-vehicle communication with greater accuracy and a data rate of more than 50 MBPS [12]. The major goal of artificial intelligent neural networks (AINN) for ML is to interact with wireless communications structural design [13].

NOMA has drawn significant attention in 5G because it can be integrated with other techniques to improve the system efficiency. The combined value of NOMA and MIMO can be precisely chosen to ensure future demand for large wireless networks with extremely high data rates and low latency [14-16] because MIMO can increase the order of diversity which in turn improves the SNR and throughput of the system. The capacity region of the channel is enhanced using multi-user superposition transmission (MUST) at the base station (BS). Hence, it enables the simultaneous serving of all the users on the same Orthogonal Frequency Division Multiple Access (OFDMA) subcarriers.

This work proposes to use ML, specifically the DLS algorithm, for OPA in MIMO-NOMA technology in order to improve system performance. By examining the two-user and multi-user scenarios, we implement OPA to a poor signal strength user (weak) via direct method of optimization and with DLS procedure optimization. Then, a comparison is made for both optimization strategies.

In the downlink scenario, multiple users receive the same superimposed signal but with different signal power. Poor signal strength users (weaker) are boosted by using maximal power before applying SIC. When there are multiple weaker users, SIC strategy fails. Furthermore, allocating power to the poor signal strength user (weaker) demands higher SNR. As a result, in the multi-user scenario, we utilize a DNN along with DLS algorithm to get the optimum capacity.

The remaining article is structured in the given format as: Part II describes the traditional MIMO-NOMA system OPA. Section III explains using OPA using DNN along with DLS algorithm. Results are discussed in section IV followed by the conclusion in section V.

2. Traditional MIMO-NOMA System Optimum Power Allocation

Consider MIMO-NOMA two-user downlink system where the system has BS and the two users; one nearer to BS and other is far (end user) from BS. However, these user terminals receive the same superimposed signal but with their own individual signals strengths. Therefore, an additional OPA is required, before applying SIC so that users effectively decode their signals; the same method is applied in the case of multi-user MIMO-NOMA system. Even in multi-user case, the entire users receives same superimposed signal with distinct signal strengths. An OPA is applied to the poor signal strength users (weaker users) prior to applying SIC. In case of multiple users, more than one weak-user is found, hence OPA method becomes complex, which leads to failure of SIC. In addition, power to the weak user requires extra SNR and therefore DNN along with DLS is used to solve the above mentioned problem, and the detailed discussion on DNN with DLS algorithm is done in section III.

An OPA traditional MIMO-NOMA system is considered using downlink (DL) scenario in figure 1. The MIMO-NOMA system contains ‘i’ number of users, single BS which has ‘i’ numbers of antennas (MIMO) and all the antennas carrying information about individual users. In the system considered, ‘ith’ user is near to the BS, ‘i-1th’user is the next nearer user to the BS, in such way user1 is farthest from the BS. Figure1 shows such prearrangement, while figure 4 shows DL.

If two users are considered, then “*i*” is equal to 2.

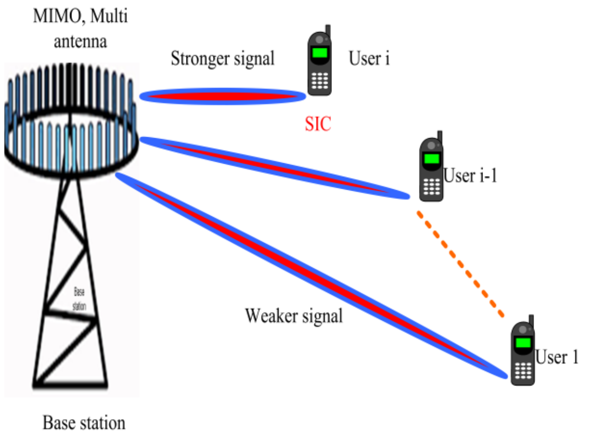

Figure 1. Traditional MIMO-NOMA system optimum power allocation.

At transmitter side, the BS generates superimposed signals, having information of distinct user terminals. This superimposed signal is broadcasted to every user. All the users obtain similar superimposed signals, but the signal strength varies depending upon the user's distance from the BS. The closest user implements SIC by decoding the distant signal first and repeat the decoding process '*i*' times, and at the end decoding its own signal, while considering remaining as noise.

The BS superposed signal is written mathematically as

$$X_s = \sum_{l=1}^{i} a_l \rho_s x_l \qquad (1)$$

Here, the signals of individual users are represented by x_l, ρ_s is the ratio of signal power to noise power (SNR) and a_l is the coefficient of power allocation. In NOMA, the SNR is $\rho_s = \frac{p_t}{\sigma^2}$, p_t is the total amount of power broadcasted and σ^2 is the white complex Gaussian noise channel's random variance.

The signal received by the i^{th} user is

$$y_i = h_i . X_s + n_i \qquad (1)$$

$$y_i = h_i . \sum_{l=1}^{i} \sqrt{a_l \rho_s x_l} + n_i \qquad (3)$$

Here, h_i is the coefficient of i^{th} user's Rayleigh fading channel and n_i is the power of noise signals $(0, \sigma^2)$.

It is proposed that the overall power allocation coefficient should be one.

$$a_1 + a_2 + a_3 + ...a_n = 1 \qquad (4)$$

For user$_1$, the maximum data rate is (According to Shannon Harley's theorem for data rate)

$$R_1 = w.\log_2\left(1 + \frac{a_1 \rho_s \beta_1}{\sum_{l=1}^{i} a_l \rho_s \beta_1 + 1}\right) \qquad (5)$$

Here w is the signal's overall bandwidth.

Since the user "*i*" is closed to BS, it decodes its signal without other interference.

Then the i^{th} user data rate is

$$R_i = w.\log_2(1 + a_i \rho_s \beta_1) \qquad (6)$$

Then the NOMA Sum-rate is given as

$$r_{x_1}^{u_1} + ... + r_{x_i}^{u_i} \qquad (7)$$

(7 (8)

$$\log_2(1 + a_i \rho_s \beta_i) + ... + \log_2\left(1 + \frac{a_1 \rho_s \beta_1}{\sum_{l=1}^{i} a_i \rho_s \beta_1 + 1}\right) \qquad (8)$$

When the number of users increases, determining a_1 minimum becomes more complex. Hence, for simplicity consider a_1 minimum. For OPA, one of the power allocation coefficients must be maximized (OPA to the poor signal strength user) and it is defined as

$$a_{1\max} \cong \frac{(1 + \rho_s \beta_1) R_1 - 1}{\rho_s \beta_1} \qquad (9)$$

$$a_{1\min} < \frac{R_i}{\rho_s \beta_i} \qquad (10)$$

With this power allocation coefficient, the weak user receives the maximum amount of power and is able to detect the signal without interference. The plot for capacity verses SNR for OPA MIMO-NOMA schemes and random power distribution MIMO-NOMA scheme has been shown in figures 2 and 3. Figure 2 depicts the capacity of two users; the i^{th} weak user capacity has increased when the maximum power is provided to it (poor signal strength user). Figure 3 shows the multi-user case and it can be seen that as the multiple users grow, the user data rate decreases, then power distribution to the poor signal strength user (weaker) necessitates a higher SNR, resulting in increase of power use. The capacity of power distribution in figure 2 is much higher than that of figure 3 which is because of the lesser number of users' utilization.

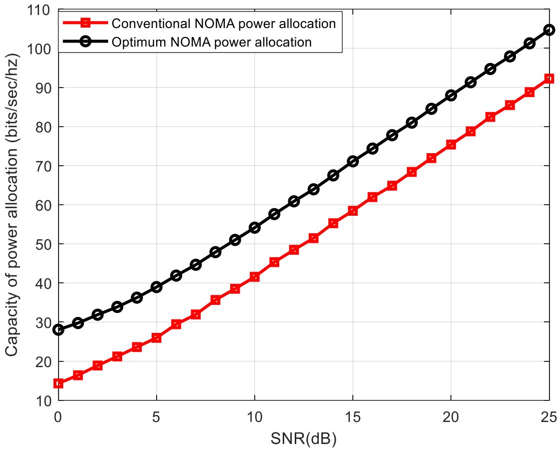

Figure 2. Two user case Capacity vs. SNR (dB); SNR ranges from 0 to 25 (dB).

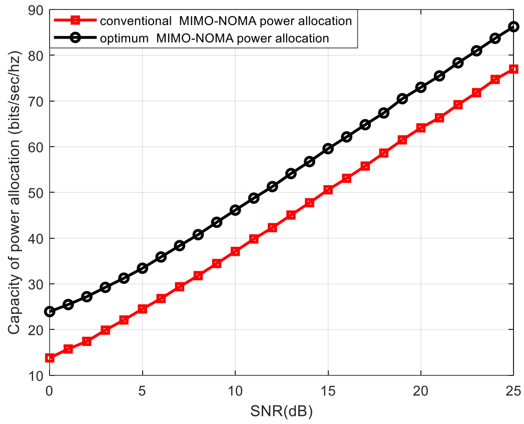

Figure 3. Multi-user case**,** Capacity vs. SNR (dB); SNR ranges from 0 to 25 (dB).

3. DNN along with DLS Algorithm for Optimum Power Allocation

In this section, OPA to weaker users using DNN-MIMO-NOMA along with DLS is discussed. The BS broadcast superimposed signal to the multiple users. Successive Interference Cancelation is applied where user decodes its signal and considers other signals as interference.

We obtain more than one weak user in a multi-user scenario therefore, SIC strategy fails. Furthermore, allocating power to the weak user necessitates a higher SNR. To tackle the above problem, a DNN along with DLS algorithm is applied in the multi-user case. Consider 'i' number of antennas at the BS; these are the DNN's input layers. Similarly, Consider '*i*' users at the output; which becomes output of the DNN. The BS sends a super positioned signal to the DNN layers, via hidden layers; then the multiple users get the super positioned signal. All users get the same superimposed signal, which may have equal strength. Therefore, it is easy to apply OPA to the weaker users using DNN and DLS algorithm. The users can now successfully decode its signal by applying SIC.

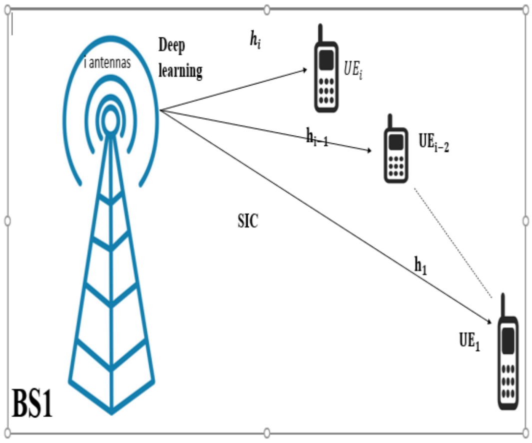

Figure 4. Multi-user OPA using DNN-MIMO-NOMA along with DLS Algorithm.

In the following section, we will discuss how to use machine learning to find the OPA. According to the authors in [9],[10],[12], ML is a simple solution for various telecommunications related challenges. It can speed up operations, provide accurate results, and reduce error rates.

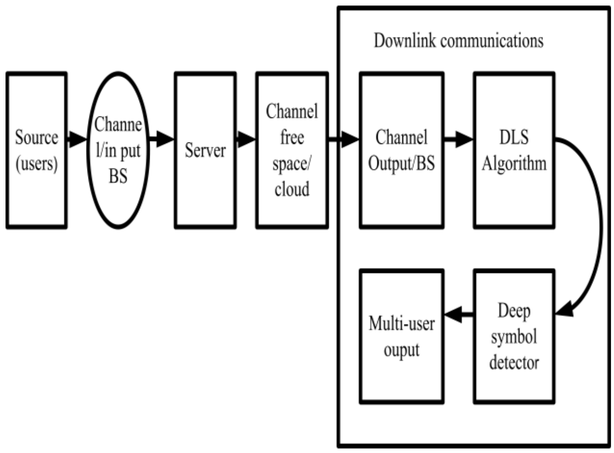

Figure 5. Communication from Source to Destinations

Figure 5 shows flow of data (source) in the downlink communication from BS to the multi-users using DNN-DLS algorithm. The DNN network has been used for transferring data to multi-users. At this stage, we need to find the long-term mean power (p_{avg}) value which is used to control power allocation strategy so that fairness in power allocation to all the weaker users is maintained. This will give the constant average total sum power rate.

Therefore, p_{avg} can be obtained from equation (8) which is represented as

$$\log_2(1+\frac{a_1\rho_s\beta_1}{\sum_{l=1}^{i} a_i\rho_s\beta_1+1})+.......+\log_2(1+a_i\rho_s\beta_i)\_R_{avg}$$

(11)

The mean power is always less than the sum of the power [13] and it is written as follows

$$P_i(t)_{\max} \geq (\frac{noisepower}{signalpower})+\frac{1}{i}\sum_{l=1}^{i} a_l\rho_s\beta_l \quad (12)$$

$$p_i(t)_{\max} > \tfrac{1}{i}\sum_{l=1}^{i-1} a_l\rho_s\beta_l \quad (13)$$

Where, $p_i(t)_{\max}$ denotes the maximum amount of power that can be given to the i^{th} user. Accordingly, $user_1$ (UE_1) which is assigned the least power decodes its signal without interference. The DLS algorithm is used to implement this approach.

Developing the DLS algorithm for NOMA OPA in DL operations [17] is explained in the coming section and the DLS algorithm's operation is presented in Figure 6.

DLS procedure for OPA in DL approach:

Inputs

$p_{avg,[X_1,X_2,X_3,......X_i]}$, size of the batch, epochs, $p_i(t)_{\max}$, bandwidth (w), OPA to poor signal strength user // learning rate

Output of DNN: allocation of power

$\{p_i, p_{i-1}, ...p_2, p_1\}$

- To provide input and output training, set the batch size to b.
- Frame a DNN structure
- Design an algorithm for DLS.
- Make a procedure for allocating optimal power
- Change the value of 'l' from 1 to i, iterates 'i' times
- Calibrate the loss function action: enter input values $\{X_i, X_{i-1}, X_{i-3}, ...X_1\}$ and produce outputs values $\hat{x}_1, \hat{x}_2, , ... \hat{x}_i$.
- OPA to the poor signal strength user
- Return $[p_1, p_2, p_{3,.............}p_i]$// optimal power distribution
- End

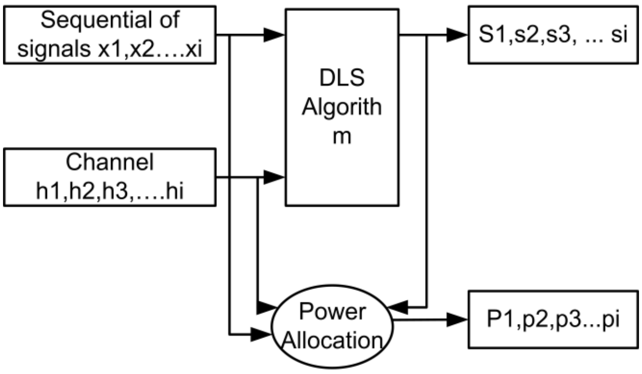

Figure 6. Optimal Power Allocation with the DLS Procedure.

The DLS procedure (algorithm) has several advantages: The best method from the DLS is Adam's algorithm having the advantages as listed below:

i. Implementation in a straightforward manner
ii. Memory requirements are lower
iii. Efficient in terms of computation
iv. The gradient is rescaled by fixed diagonals.
v. Object that is generally a non-stationary.
vi. Hyper-parameters allow for straightforward iteration and require very little adjustment.

Algorithm

Size of the batch =50, Learning Rates lr=0.01, 0.001, 0.001, 0.0001, and 0. 00001, epochs=50, total layers =7, one output, one input, and 5 Hidden Layers. Multi-cell Dataset(http://data.ieeemlc.org/dst/02/multi_cell.zip). Here multi-cell data set is used for data transmission and reception [http://data.ieeemlc.org/dst/02/multi cell.zip]. In this, data set is having a total of four data transmission input matrices, each having a size of 33000x40 bytes and a double class size of 105600000 bytes. Along with 25 output data transmission matrices, each measuring 5x330000 bytes belong to the doubles class. The complete maximum power matrix is having a double class and is 1 x 1, 8 bytes in size.

4. Deep Neural Network Operation

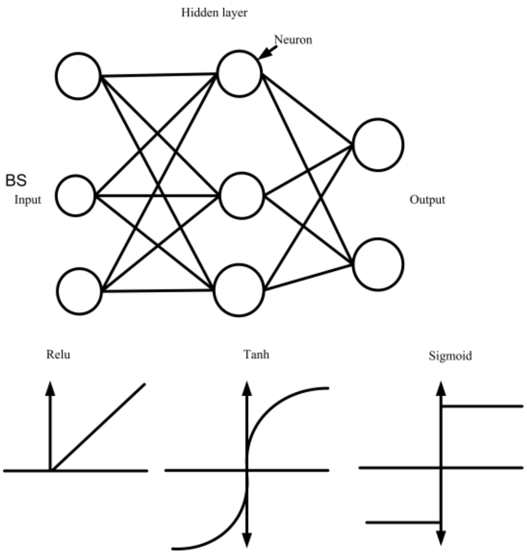

Figure7. Optimal Power Allocation using DNN and DLS

Figure 7 shows that the BS transmitter assigns input values, the batch is decided based on input samples, each with hidden layer neurons and the hidden layer input density [18]. Our major goal is to get the '*i*' users (many users) to the output layer via hidden layer. Let us consider the function $f_i(x_i)$ with *i* users, which consists of input layers, numerous hidden layers, and output layers. Operation of such arrangement is defined in [19], [20] as:

$$\{e_{i,n_i}(w_{i,n_i}....e_{i,1})(w_{i,1}x_i+b_{i,1})....(b_{i,n_i})\}=f_i(x_i) \quad (14)$$

Here, total layers is defined as n_i, and $b_{i,n_i}, w_{i,n_i}, e_{i,n_i}$ indicates biases vector , weight of the matrix, activation function, in the mth layer, respectively. The m value ranges from 1 to i, x_i is the i^{th} user's signal input. In order to obtain the loss between layers, loss function is required. The probability of SINR is minimized in each user when extended to large number of layers. As a result, maximum power transfers to the weak signal strength user takes place successfully.

The difference between the predicted and real value is the DNN's loss function [19], [21].

$$L(\theta,v_i)=\sum_{i=1}^{I}\frac{1}{x_I}\sum_{x_i=x_I}((X_s-R_i\{X_s\},\theta,v_i)^2) \quad (15)$$

Here, v_i,θ are the precoder biases and weight function, respectively, total input samples are represented as X_s, and the ith user decoding signal is ($R_i\{X_s\},\theta,v_i$). Gradient descent method is used to minimize loss function and it changes from

$$(\theta,v_I)\rightarrow\begin{pmatrix}\theta-\beta\delta L_\theta\{\theta,v_i\}\\ v_I-\beta\delta L_{v_i}\{\theta,v_i\}\end{pmatrix} \quad (16)$$

Here $\beta>0$ for all possible values of 'i', the gradient descent value of the (θ,v_i) are $\delta L_\theta\{\theta,v_i\}$, $\delta L_{v_i}\{\theta,v_i\}$. The original data set is collected from [22].

5. Result and Discussions

In the DNN training approach, {1, 2, 3, 4} are chosen as cell indices. The allocated sample set for various layer considered in the proposed approach is represented in the table 1. For this operation, we have considered batch size as 60 so, allotted batch size = 60. Adam's OPA is considered as beta_1= 0.01 and beta_2=0.999. The Learning Rate (LR) of input changes from layer to layer, hence LR_1=0.01, LR_2 = 0.001, LR_3 = 0.0001, LR_4 = 0.00001, LR_5 = 0.000001 and LR_6 =0.000001 respectively. For a small change in weights and biases values, the minimum delta value is required, that is delta _min =0, and under split validation, for any LR, delta value assumed to be the same. Split Validation=0.03125, under this, all activation functions are considered as rectified leaner unit (ReLU). The actual Github's multi-cell data set is modified and served into the DNN along with DLS algorithm.

Input vector size (40, 330000)
Output vector size (5, 330000)
Model: "sequential_3"
Overall parameters: 285,219
Trainable parameters: 285,189
Non-trainable parameters: 30

Table 1. Parameters values in Input- Output samples

Layer(type)	Shape of output	#Parameters
(Dense)Layer1	(None,512)	20992
(Dense)Layer2	(None,256)	131328
(Dense)Layer3	(None,256)	65792
(Dense)Layer4	(None,256)	65792
(Dense)Layer5	(None,5)	1285
(Dense)Layer6	(None,5)	30

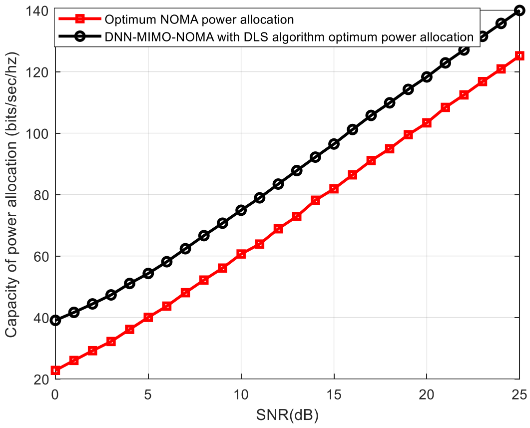

Figure 8. Power allocation Capacity vs. SNR (dB) of the proposed method in multi-user scenario.

The power allocation capacity is observed in the figure 3 and figure 8 in terms of SNR (dB). Power allocation capacity is more when DNN is applied along with DLS algorithm. For all scenarios, we consider the range of SNR from 0 to 25(dB). At SNR 20 dB and 25 dB, the DNN-MINO-NOMA has achieved an OPA capacity of 120 bits/sec/Hz and at 25 dB it achieves 140 (bits/sec/Hz). It has been observed that the optimum power reduces with the increase in the number of users in the system.

6. Conclusion

In this article, an OPA to the weak user is implemented in various scenarios such as two user OPA, multi-user OPA and multi-user OPA using DNN along with DLS algorithm. In two user and multi-user case, it is observed that the power allocation capacity reduces on increasing the numbers of users in the system. In two user scenario, capacity of power allocation is more compared to the multi-user. Power allocation capacity using DNN with DLS algorithm is more in compared to the system without-DNN with DLS algorithm in Multi-user OPA. It is concluded from the cases discussed so far that the OPA using DNN along with DLS algorithm achieved the OPA capacity. Future research will focus on allocating optimum power to weaker user with Deep learning MIMO-NOMA with GRU/LSTM layers and different algorithms.

7. Appendix

The data rate for 'i' users is

$$\log_2\left(1+\frac{a_1\rho_s\beta}{\sum_{l=1}^{i}a_i\rho_s\beta_1+1}\right)+\ldots+\log_2(1+a_i\rho_s\beta_i) \quad \text{(A1)}$$

We assume no. of users, i=2

$$sum=\log_2(1+a_i\rho_s\beta_i)+\ldots.+\log_2\left(1+\frac{a_1\rho_s\beta_1}{\sum_{l=1}^{i}a_i\rho_s\beta_1+1}\right) \quad \text{(A2)}$$

To obtain the dependent function values equation (A.2)

$$\log_2\left(1+\frac{a_1\rho_s\beta_1}{1+a_2\rho_s\beta_1}\right).(1+a_2\rho_s\beta_1) \quad \text{(A.3)}$$

Total power allocation coefficient is unity

$$a_2=-a_1+1 \quad \text{(A.4)}$$

Substitute a_2 in equation (A.3)

$$\log_2\left(1+\frac{a_1\rho_s\beta_1}{(-a_1+1)\rho_s\beta_1+1}\right).\{(-a_1+1)\rho_s\beta_2+1\} \quad \text{(A.5)}$$

$$\log_2(1+\rho_s\beta_1).\left[\frac{\{(-a_1+1)\rho_s\beta_2+1\}}{\{(-a_1+1)\rho_s\beta_1+1\}}\right] \quad \text{(A.6)}$$

Here, $1+\rho_s\beta_1$ is constant

$$\left(\frac{\frac{1}{a_1}+\frac{\rho_s\beta_2}{a_1}-\frac{\rho_s\beta_2}{1}}{\frac{1}{a_1}+\frac{\rho_s\beta_1}{a_1}-\frac{\rho_s\beta_1}{1}}\right) \quad \text{(A.7)}$$

If a_1=0, then the equation (A.7) is invalid. Hence, L-Hospital's rule is used to convert it into a valid function. Partial derivation is applied independently in numerator and denominator in equation (A.7).

$$\frac{\frac{1}{a_1^2}-\frac{\rho_s\beta_2}{a_1^2}-0}{\frac{1}{a_1^2}-\frac{\rho_s\beta_1}{a_1^2}-0} \quad \text{(A.8)}$$

$$\frac{1-\rho_s\beta_2}{1-\rho_s\beta_1} \tag{A.9}$$

In order to maximize the function, consider β_1 maximum and β_2 minimum. To obtain the a_{1max} maximum value from equation (A.10). It is assumed that the data rate is greater than or equal to R_1.

$$\log_2(1+r_{x_1}^{u_1}) \geq R_1 \tag{A.10}$$

$$1+r_{x_1}^{u_1} \cong 2^{R_1} = \hat{R}_1 \tag{A.11}$$

From equation (A.4)

$$a_1\rho_s\beta_1 + \hat{R}_1\, a_1\rho_s\beta_1 = \hat{R}_1(1+a_1\rho_s\beta_1) \tag{A.12}$$

$$a_{1\max} \geq \left[\frac{\hat{R}_1(1+a_1\rho_s\beta_1)}{\beta_1\rho_s(1+\hat{R}_1)}\right] \tag{A.13}$$

Such that, from the 'i 'number of users

$$\log_2\left(1+\frac{a_1\rho_s\beta_1}{\sum_{l=1}^{i-1} a_i\rho_s\beta_1 + 1}\right) \tag{A.14}$$

$$1+r_{x_1}^{u_1} \cong 2^{R_1} = \hat{R}_1 \tag{A.15}$$

$$\frac{a_1\rho_s\beta_1}{\sum_{l=1}^{i-1} a_i\rho_s\beta_1 + 1} = R_1 - 1 = \hat{R}_1 \tag{A.16}$$

Total power allocation coefficient is unity, so

$$\sum_{l=2}^{i} a_l \cong 1 \tag{A.17}$$

$$\frac{a_1\rho_s\beta_1}{\rho_s\beta_1+1} = R_1 - 1 = \hat{R}_1 \tag{A.18}$$

a_{1max} is obtained from the equation (A.18)

$$a_{1\max} \geq \frac{\hat{R}_1(\rho_s\beta_1+1)-1}{\beta_1\rho_s} \tag{A.19}$$

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