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User Selection and Pairing for Future Power Domain Non-Orthogonal Multiple Access (PD-NOMA) using Deep Learning Techniques

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Abstract

The next-generation wireless networks and communications such as 5G/6G offers various benefits such as low latency, high data rates, and improvement in user numbers with increased base station capacity and quality of service. These advantages are obtained from the increasing receiver complexity through the non-orthogonal multiple access (NOMA) of users. It is the promising radio access approach used to enhance next-generation wireless communications. Among the techniques of NOMA such as power and code domain, this paper concentrates on power domain NOMA. The user in the network for transmission is selected using a deep learning approach called deep neural network (DNN). This user selection results are the training data and the loss function is modified for the selection of users that could meet the constraint the selected user cannot be in both strong and weak groups. The user aggregation/user pairing among the sub-channels is performed through the exhaustive analysis using particle swarm optimization (PSO). The usage of DNN-PSO enables the transmitter and required minimum uplink and downlink transmitting power and guaranteed for Quality of Service of each user. The simulation and comprehensive statistical evaluation are performed with the comparative analysis of energy efficiency and maximum achievable rate with the given spectrum efficiency (SE) of PD-NOMA. The proposed model ensures reduced latency, increased throughput, less energy, achievable data rate, user fairness and increased reliability and quality of service.

Keywords: Non-orthogonal multiple access (NOMA), power domain, Deep neural network (DNN), Particle Swarm Optimization (PSO), wireless networks.

I. Introduction

The diffusion of the multimedia devices such as tablets, smartphones, and laptops are grown rapidly during the last decade. Based on the wireless world research forum, there are seven trillion wireless devices are serve seven billion people in 2020. The rapid growth of this mobile internet and IoT (Internet of Things) accelerates the generation and transmission of the huge volume of data that demands a high data rate with reduced latency applications. In contrast, these devices share a limited number of resources which leads to network data traffic. Hence, new wireless communication technologies such as 5G and 6G are needed. In order to solve the consumer demand for increasing wireless data, wireless transmission-based research is evolving continuously. This efficient management of resources needs resource allocation approaches that include user selection. In addition, Non-Orthogonal Multiple Access (NOMA) can overcome these issues and provides a high data transmission rate which provides promising solutions in 5G network and more. In NOMA, more than one user can share the same resources with higher bandwidth than Orthogonal Multiple Access (OMA) [1]. The multiple signals are gathered and transmitted over the Serial Interference Cancellation (SIC) approach used by the receiver [2].

NOMA can be combined with wireless communication technologies to obtain the requirements such as high spectral and energy efficiency, low latency, increased throughput, quality of service, massive connectivity, improved transmission of data rate, and user fairness. NOMA supports multiple user data transmission in a single resource block. It is categorized into Coded domain NOMA and Power domain NOMA. This paper concentrates on the power domain NOMA (PD-NOMA). In PD-NOMA, various signals are transmitted to various users which are multiplexed with the Superposition Coding (SC) method at the base station (BS) with various transmission power. The strong users (high channel gain) are allocated with less power and weaker users (low channel gain) are allocated with more power. Using the power allocation approaches, the strong users can suppress the Signals using a SIC receiver that decodes the dominant interfering signals and subtract them from the superposed signal. For the weak user set, the interfering signals are discarded since the stronger user power is allocated as low.

Tseng et al., [3] developed a user selection approach in NOMA with multi-antenna beam forming for video communications. They used Deep Neural Network (DNN) based on optimal user selection with a modified cost function for user selection. They overcome the issues that the user cannot be in both strong and weak sets. The simulation results show better performance than other state-of-the-art methods in terms of Peak Signal to Noise Ratio (PSNR). Masaracchia et al., [4] developed Particle Swarm Optimization (PSO) based user grouping in NOMA which meets the minimum downlink transmission power constraint. They evaluated this method in two power-constrained applications such as disaster relief networks and unmanned aerial vehicles (UAV).

Faeik et al., [5] developed uplink PD-NOMA which estimates bit error rate (BER) using the channel estimation errors for 5G. They used various modulation schemes such as BPSK, 16-QAM and QPSK. The simulation in terms of SNR evaluation shows that QPSK performs better than other approaches. Kumaresan et al., [5] developed a user clustering approach for downlinking PD-NOMA using DNN that efficiently manages the power allocation. This DNN-based user clustering method characterizes the nonlinearity between transmission power and channel diversity. The evaluation in terms of Mean Square Error (MSE) and throughput and comparison among Artificial Neural networks, shows that DNN-based user clustering performs better with increased throughput. The work in [4-7] started to use ANN and DNN for user selection in NOMA with the available datasets to improve the QoS of wireless communication systems. However, the implementation of deep learning (DL) with evolutionary algorithm-based cost optimization is not researched and this motivates us to concentrate on DL with PSO for user selection that can ensure to increase the throughput and reduce the latency and energy of the upcoming wireless networks. The major contribution of this work is as follows:

- In NOMA, for user selection and grouping, a deep learning-based model called Deep Neural Network with Particle Swarm Optimization (DNN-PSO) has been proposed.
- The proposed PD-NOMA is trained with DNN and the trained model is validated through Mean Square Error (MSE) in the testing phase.
- In order to minimize the MSE and increase the throughput, the hyper parameters are optimized using an evolutionary algorithm called PSO which obtains the balance between MSE and throughput. The implementation of different activation functions such as ReLU, Sigmoid, and Softmax are analyzed.
- The learning rate and a number of epochs are tested against throughput and it is fixed based on improved throughput results.
- The capability of the proposed model is simulated and demonstrated in terms of increased throughput and reduced energy and the results are compared with existing NOMA environments.

The remaining section of this paper is as follows: Section 2 discusses the NOMA-based related works. Section 3 discussed the proposed system model and methods for PD-NOMA user selection. Section 4 demonstrated the experimented results and evaluation and Section 5 concludes the proposed work with its advantages and issues.

II. Related Work

This section discusses the related research work of NOMA. Hussain et al. [8] discussed the NOMA's technical aspects with its research direction for next-generation mobile networks. They compared NOMA with OMA and reviewed the NOMA schemes. This scheme's performance is compared in terms of BER, energy efficiency, and system capacity. Rajab et al., [9] analyzed the PD-NOMA with Device to Device communication using the Greedy Asynchronous Distributed Interference Avoidance Algorithm (GADIA) as a frequency allocation approach. They compared the experimented results in terms of energy efficiency and achievable data rate with orthogonal frequency division multiple access (OFDMA). Luo et al., [10] developed a deep learning-based resource allocation approach for downlinking simultaneous wireless information and power transfer for MC-NOMA system with PDMA. They demonstrated that DL-based approaches reduce the computation time and power consumption with its exhaustive search criteria. Akbar et al., [11] reviewed about 5G and NOMA technologies, issues, and their challenges. They discussed the combination of PD NOMA with the emerging applications including Multiple-input multiple-output (MIMO), Heterogeneous networks, simultaneous wireless information, and power transfer, cooperative communication, mobile edge computing, visible light communication, UAV, and intelligent reflecting surfaces.

Yahya et al., [12] reviewed the error rate of NOMA with its principles and future directions. Kumaresan et al., [13] developed a PSO-based user clustering for NOMA. This will reduce the computational complexity and increase the throughput of the system. They concentrate on the

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particle early convergence problem in the search space for a larger NOMA network. Lin et al., [14] developed a model based on DNN to analyze the channel state information and detect real transmit sequences. They combined channel estimation and channel distortion for multi-user signal superposition. Pan et al., [15] investigated the robustness of the high order modulation techniques in order to enhance the NOMA sum rate and imperfect SIC using DNN proposed by Yang et al., [16]. The work [16] does not cover the dynamic user change. It is enhanced by Pan., which obtained optimal performance among machine learning approaches. DL model secured nonlinear transformation and results in user clustering prediction with optimal throughput.

III. Proposed System Architecture

Yahya PD-NOMA is the key technology in the wireless communication system that can distribute the power and the technology called SIC allows various users to share their resources such as frequency rate, time and so on. The system performance is improved in terms of energy efficiency and throughput as a result. This section discussed and proposed the subsection such as (i) System model as the introduction about Uplink NOMA and downlink NOMA where how the SIC and SC are implemented (iii) proposed formulation of deep learning and optimization for user selection and pairing. Fig 1 illustrates the proposed system management process of uplink and downlink NOMA. There are various users who send their signals to the base station (BS) in the same resources in uplink transmission. The users are selected and paired using the proposed DNN with the PSO model. With the assistance of SIC, BS identifies the user messages. The transmit power of uplink and downlink NOMA are not different. It is based on each user channel condition, if it differed then the SINR may differ a bit at the BS.

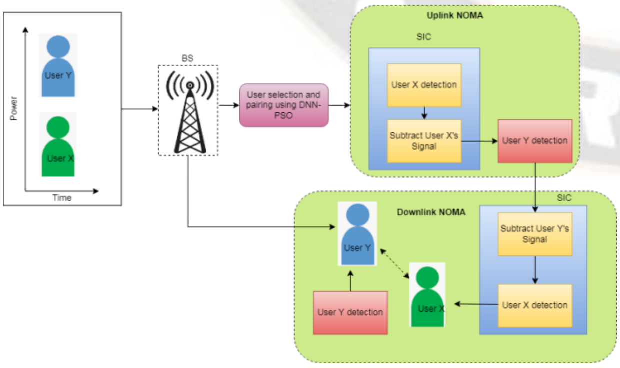

Figure 1 – The proposed architecture of user selection and pairing of PD-NOMA

The SIC operations of uplink and downlink NOMA also differed. From Fig 1, the user X signal is disinfected with the interference from user Y. This is performed with the detection of user Y's powerful signal, modulating it, and deducting from the composite signal. In the downlink, SIC is performed on strong user and cancel the weak user interference. By contrast, in uplink NOMA, the SIC operation is performed in BS which differentiates the strong user X by treating the user Y as interference. Then the recovered signal is demodulated and interference is subtracted to identify the user X.

System Model

The proposed system model consists of one base station (BS) and n wireless network users such as U_1, U_2,…U_n. The user U_1 is closest to BS with the best condition of the channel, and U_n is the edge of the BS with the worst condition of the channel. For two user transmission, U_1 send message directly to U_2 through the base station and SCI helps to deduct the user messages. For n number of users, U_2 acts as a relay node of U_1, while U_2 is directly communicates to U_3 as Device to Device communication. The signal transmitted by BS is written as in Eq. (1)

$$X(t) = \sum_{n=1}^{N} X_n(t)\sqrt{\gamma_n p_t} \tag{1}$$

Where, p_t-transmit power of the base station, γ_n- power allocation factor for each user U_n which is stated in Eq. (2)

$$p_n = \gamma_n p_t \tag{2}$$

The received signal in the user U_n is stated in Eq. (3)

$$Y_n(t) = h_{bs}.X(t) + w_{gn} \tag{3}$$

Where, w_{gm}- Gaussian white noise,h_{bs} channel from base station to U_n. U1 detects $X_n(t)$ and remove the interference signal to $Y_n(t)$ and detect$X_{n-1}(t)$ and eliminates the interference signal to $Y_n(t)$ until X_1 is checked. Hence, the SINR for U_n is written as in Eq.(4)

$$SINR_n = \frac{p_n|H_{bs}|^2}{\sum_{i=1}^{N-1} p_i|H_{bs}|^2+1} \tag{4}$$

The throughput of user in bs is stated as in Eq. (5)

$$R_n = Blog_2[1 + SINR_n] \tag{5}$$

Where B – transmission bandwidth. The fairness index f is written as in Eq. (6)

$$f = \frac{(R_n)^2}{N\sum R_n{}^2} \tag{6}$$

The Eq. (6) denotes the sharing system fairness capacity among the users. When f is 1 then user capacity close to each other. Based on these condition, the power allocation also maximizes the NOMA capacity. This can be treated as a nonlinear optimization problem which is described as follows:

$$\max R_n \; where \;\; f \geq f', p_n \geq 0 \; \forall n, \sum_{n=1}^{N} \gamma_n \leq 1^{\gamma_n} and \; \sum_{n=1}^{N} p_n \leq p_t \tag{7}$$

Where f' – target fairness index.

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User Selection and pairing using DNN and optimized with PSO

The network users using NOMA are selected using fully connected deep neural network (FCDNN) which consists of input layer, more than one hidden layers and an output layer. The output layer is divided into strong set and weak set selection. The Fig 2 shows the architecture of FCDNN.

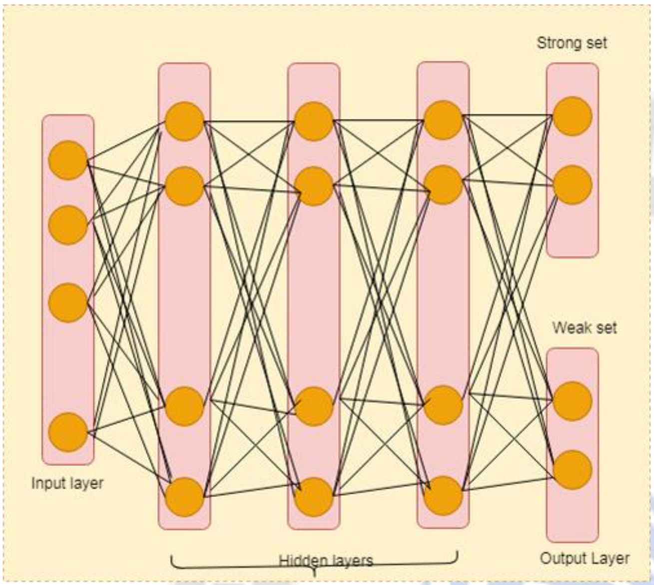

Figure 2 – FCDNN Structure

The channel gain from physical layer and function parameters from the application layers are given as input to the Neural network (NN) and the output layer is the user selection and pairing result which is denoted as 2 × M matrix. The first row of the matrix 1 × M represents there are n users have been selected in the weak set. It is possible to be the user in both groups. For FCDNN, the data are need to be in one dimensional, hence the output data is resized into 1× 2M matrix. The FCDNN input and output pair for the training data is generated as follows: for FCDNN, the inputs are the channel coefficients of the training data which are generated randomly based on independent probabilistic model. The training data output is the 1× 2M resource allocation matrix obtained from the resource allocation algorithm called Scheme Optimal [17]. The testing data also generated as the same way. The generation of channel coefficients are based on probabilistic model which is differ from training data.

The parameters of the FCDNN is represented as $\alpha = [\alpha_1, \alpha_2, \dots \alpha_L]$. The parameter set of the layer l is $\alpha_l = \{w_l, b_l\}$ where w and b are the weight and bias of lth layer neuron respectively. the layer l is denoted as in Eq. (8)

$$y_l = \sigma(w_l x_l + b_l) \tag{8}$$

Where, σ- activation function. In this work, ReLU (Rectified Linear Unit) is used as an activation function as in Eq.(9) for each layer except output layer. In output layer softmax activation function is used.

$$\sigma_{ReLU}(x) = \max(0, x) \in [0, \infty] \tag{9}$$

The user combinations are numbered and the pre trained data are send to FCDNN training data as numbers. After training, the numbers are converted into its original data type. In order to improve the accuracy of the model, the real training data use sigmoidal activation function as in Eq. (10)

$$\sigma_{sigmoid}(x) = \frac{1}{1+e^{-x}} \in (0,1) \tag{10}$$

For this classification problem, binary cross entropy [3] function is used as loss function with the fairness loss constraint stated in Eq. (11)

$$Loss = L(w, b) + L_{constraint} \tag{11}$$

$$L(w, b) = \frac{1}{N}\sum_{i=1}^{N} -[y(i)\ln(y_L(i) + (1 - y(i))\ln(1 - y_L(i))] \tag{12}$$

Where $y(i)$- desired output and $y_L(i)$- FCDNN output of training data. In the NOMA, the user are in both sets. To avoid this situation of FCDNN output and reduce the computational complexity, the loss function is modified with the constraint as in Eq. (13) and optimized with evolutionary algorithm called PSO.

$$= \begin{cases} L\_constraint = 0.5 \text{ if user is common in strong and weak set} \\ L\_constraint = 0, \text{ otherwise} \end{cases} \tag{13}$$

During the training of FCDNN, the loss function is minimized using PSO and it will avoid the situation of user is common in both sets.

The Particle Swarm Optimization (PSO) was developed by Kenned and Eberhart in 1995 which is widely used optimization technique due to its efficiency [18]. In PSO, each individual of the population is called as particle which consists of its position, velocity vector and fitness value to control the particle movement. Based on the internal intelligence (pbest) and best experience (gbest). Each particle performance is evaluated using the predefined cost functions at the end of the iterations. The work flow of PSO is illustrated in Fig 3. Among the whole population, each particle takes neighbor particle value referred as optimal global value called Gbest. The PSO process is calculated using the Eq.(14) and (15)

$$v_i^{t+1} = wv_i^t + c_1.r_1(Pbest_i^t - x_i^t) + c_2.r_2(Gbest^t - x_i^t) \tag{14}$$

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$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (15)$$

Where, i= 1…N – no. of swarm population. v_i^t- velocity vector, t- iteration, x_i^t – current position of i^th particle, $Pbest_i^t$- previous best position of i^th particle, $Gbest^t$- previous best position of whole particle, c_1 and c_2 – coefficients called cognitive parameter an social parameter, r_1,r_2 ∈ [0,1]- random numbers, w- internal coefficient to control the local and global search. The standard PSO can update the position of the particle using the Eq. (16)

$$x_i = \begin{cases} 1 & if\ rand < s(v_i^{t+1}) \\ 0 & otherwise \end{cases} \quad (16)$$

Where $s(v_i^{t+1})$ is the sigmoid function that will transform the velocity into the range (0,1), rand()- random number selected from the distribution in the range [0,1]. The normal fitness function in the Eqn (17) is used to minimize the classification error during the training process.

$$fitness\ function\ f = Error\ rate = \frac{FP+FN}{TP+TN+FP+FN} \quad (17)$$

In this work, the initial particle set is formed randomly. For each user U, random number in the range 0 to 1 such as UCH1 is extracted. All the sub channels are numbered from 1 to N, the channel ID of user Ui is obtained from ceil function as in Eq. (18)

$$UCH_{ID,i} = ceil(UCH_i \times N) \quad (18)$$

The evaluation of $Pbest_i^t$ of each particle is used to reduce the power consumption of the downlink NOMA and each particle goodness value is evaluated with the fitness function. From Eq. (15), if the result is less than zero, another number is extracted randomly. If it is greater than 1, the value of one is assigned. The boundaries of the network is set as minimum and maximum velocity.

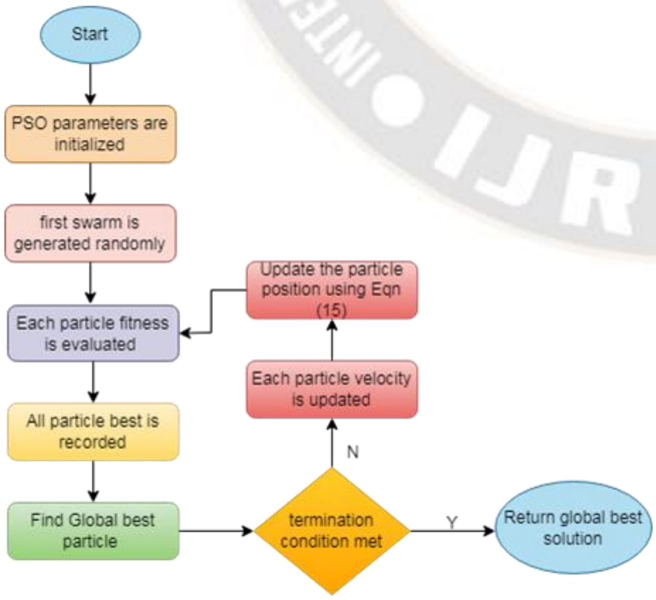

Fig.3. PSO algorithm- flowchart

Energy of proposed method

The energy efficiency of this proposed model is considered as downlink where $E_{total}$is the total energy consumption by the BS which is written as in Equation (19),

$$E_{total} = E_s + E_t \quad (19)$$

Where, E_s – consumed power due to hardware and signal processing, E_t – consumed power of signal transmission. Hence, the total transmission power is the sum of signal transmission power and energy consumed. Energy Efficiency is the ratio between throughput and total power as in Eq. (20)

$$E = \frac{R_{throughput}}{E_{total}} \quad (20)$$

IV. Simulation Results and Discussions

In this section, the proposed model is evaluated with the simulation and compared with various NOMA environments. For simulation of the proposed model, the training data are collected and gathered from [19] without limited sample issues. These data are balanced because the channel coefficients of each user at various slots are generated randomly based on probabilistic model. The proposed model is based on deep learning and evolutionary algorithms, MATLAB tool is used to model the NOMA channels. The simulation parameters are listed in Table 1.

Table 1.Simulation Parameters of the proposed model

Parameter	Value
Cell radius	200m
Average number of nodes	N=100
Bandwidth	45MHz
Pathloss exponent	γ=4
No of sub channels	[50:100]
Batch size	30,60,90,120,150
Learning rate	0.01, 0.02,0.002, 0.001
Number of hidden layers	3
Hidden layer activation function	ReLU
Output layer activation function	Sigmoid
Epochs	250
Training data	24000
Validation data	6000
Testing data	3000

Based on the training data loss and validation loss, number of epochs have been selected as illustrated in Fig 4 and Fig 5 respectively.

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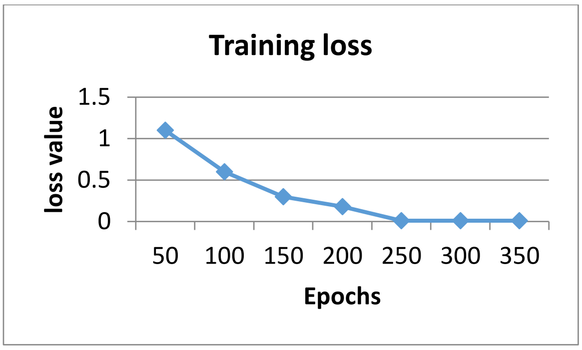


Fig.4. Loss vs Epochs of training data

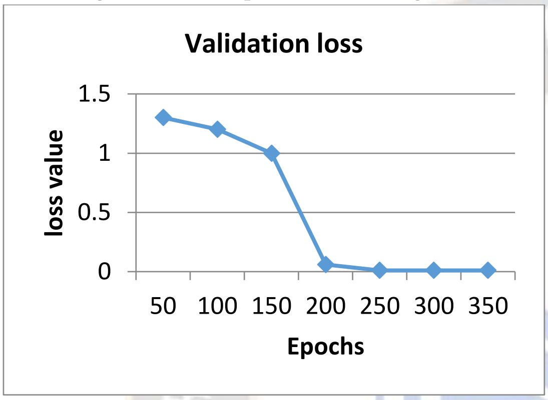


Fig.5.Loss vs Epochs of validation data

The observation from these illustrations is as follows: the loss function value is not changed after 250 epochs, hence the epochs are fixed as 250 in table 1. In validation loss value, there is no change in the value after 250 epochs as in training and also there is no overfitting issue occurs. The DNN can learn correct sample of training and validation data. The loss constraint of DNN also validated.

The proposed model is compared with other NOMA systems in terms of the comparison metrics of desired and simulated PSNR value. The desired PSNR is computed using the Eq. (21) and (22). The simulated PSNR is computed using MSE for simulation and consider imperfect source encoding rate, channel included errors etc.

$$MSE_{PD-NOMA} = a_n + \frac{b_n}{R_{PD-NOMA}+c_n} \quad (21)$$

Where, a_n,b_n and c_n- before transmission these values are fitted based on input, $R_{PD-NOMA}$ is the rate of the proposed model as in Eqn (5) to indicate the strong and weak user set. The Peak signal to noise ratio (PSNR) is computed as in Eq. (22) where Max (f) is the maximum signal value of original input.

$$PSNR = 10 \times \log_{10} \frac{Max(f)}{MSE} \quad (22)$$

The proposed DNN-PSO based PD-NOMA model is comparedwith the existing approaches such as (Scheme 1) DNN based user selection [3], (Scheme 2) PSO based user grouping for NOMA [4] and (Scheme 3) GADIA based resource allocation for Device to Device communication [9]. The comparative PSNR value of the image and video inputs based NOMA is shown in Fig 6 and Fig 7. From Fig.6, all the NOMA schemes average theoretical PSNR values are shown. It has been observed that the proposed scheme is perform best compared to other approaches. The proposed DNN based learning and PSO based cost enhancement secured 34dB of PSNR value. Various the other approaches secured 28dB, 30dB and 32dB respectively. Scheme 1 secured the minimum PSNR value.

It is shown that simulated PSNR values for all the schemes lower than theoretical PSNR value due to channel errors, source encoder, imperfect rate control and etc.,. The observed results from Fig.7 shows that proposed scheme outperforms than other approaches. The proposed DNN based learning and PSO based cost enhancement secured 33dB of PSNR value. Various the other approaches secured 27dB, 29dB and 31dB respectively. Scheme 1 secured the minimum PSNR value.

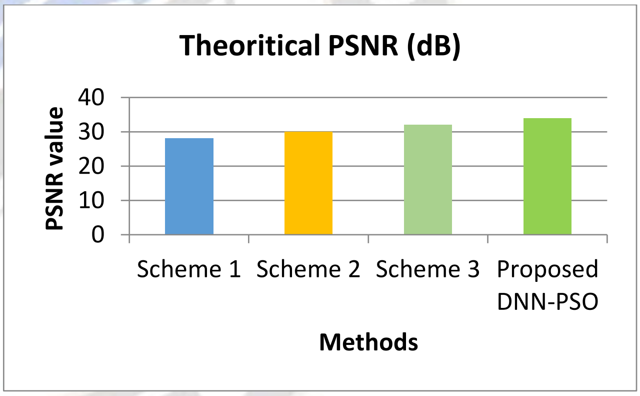
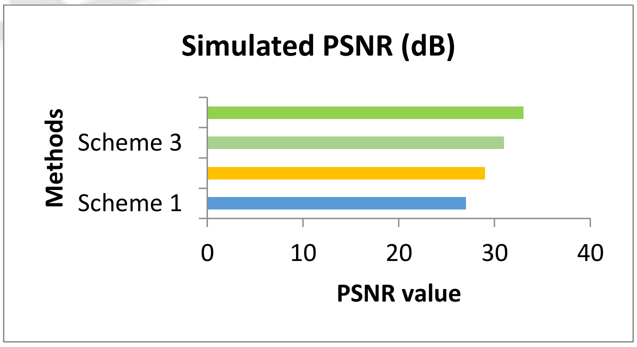


Fig.6. Theoretical PSNR comparison of proposed vs existing NOMA schemes



(22)
Fig.7.Simulated PSNR comparison of proposed vs existing NOMA schemes

The comparative analysis in terms of number of users and throughput is shown in Fig 8. The proposed model with sigmoid and ReLU activation function secured improved throughput among various users such as 10, 20, 30, 40 and 50.

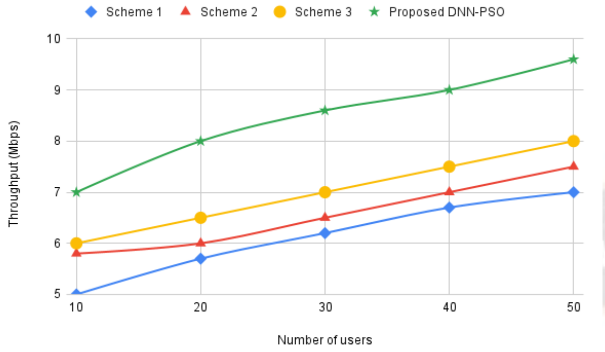


Fig.8. Throughput comparison of proposed vs existing NOMA schemes

For 50 number of users, the proposed DNN-PSO based NOMA scheme secured the throughput of 9.6Mbps. Various the other existing NOMA schemes such as Scheme 1, Scheme 2 and Scheme 3 secured 7Mbps, 7.5Mbps and 8.1Mbps respectively. The learning rate for the DNN model is fixed based on the analysis of various learning rate comparisons in terms of throughput. These analyzed results are shown in Table 2.

Table 2: Performance of proposed approach in terms of throughput for various learning rate

Learning rate	Epoch			
	50	100	150	200
0.01	5	5.8	6	7
0.02	5.7	6	6.5	8
0.002	6.2	6.5	7	8.6
0.001	6.7	7	7.5	9

From table 2, the learning rate for the proposed DNN is fixed based on the throughput results at various epochs. The proposed model secured reduced loss at epoch 200 and now the deep learning model with various learning rate such as 0.01, 0.02, 0.002 and 0.001 is tested against throughput. The improved throughput value is obtained at the learning rate of 0.001 in all the epochs. Hence, at 0.001 learning rate, the proposed model performs better. The evaluations in terms of energy efficiency for all the schemes are illustrated in Fig 9.

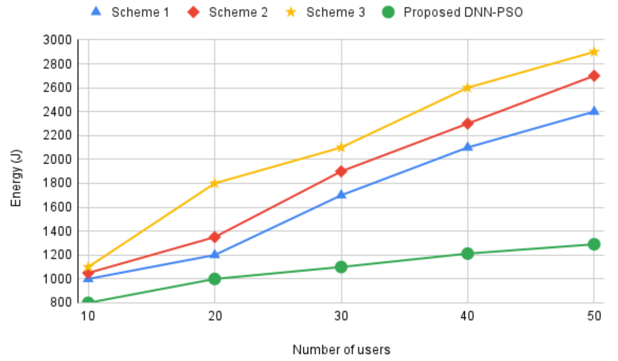


Fig. 9.Energy comparison of proposed vs existing NOMA schemes

The illustration from Fig 9 proves that the proposed scheme secured less energy for all the users compared to existing methods. The proposed model secured 1290J for 50 number of users. For the same, the existing schemes secured 2400J, 2700J and 2910J respectively. This analyzed result proves that the proposed model is efficient with less energy consumption due to the implementation of evolutionary approaches. Hence, the parameters for the model is fixed under various analysis as well as the performance of the proposed model is evaluated in terms of noise, throughput and comparative analysis.

V. Conclusions

In this paper, Deep learning with evolutionary approach called DNN-PSO has been proposed for user selection and pairing in PD-NOMA for next generation wireless communication networks such as 5G/6G. With the generated dataset, the proposed model is trained, validated and tested. The various evaluations in terms of loss, PSNR, throughput, learning rate selection and energy proves the efficiency of the proposed PD-NOMA model. The number of epochs is selected based on training and validation loss. The values are convergence after 200 numbers of epochs. In terms of image and video data transfer, the noise must be reduced and the best model must have increased PSNR value. The proposed model is evaluated in terms of theoretical PSNR and simulated PSNR metrics and secured improved PSNR value of 34dB and 33dB respectively. The evaluation in terms of throughput, the proposed model secured 9.6Mbps for 50 numbers of users. Compared to other approaches, the proposed model is superior and performs better. With the learning rate of 0.001, the proposed model performs better and it is evaluated based on throughput and number of epochs. Finally, the energy efficiency of the NOMA schemes are evaluated and the results shows reduced energy of 1290J for 50 number of

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users. Hence, the evaluation and comparison proves that the proposed model secured reduced energy with increased throughput and it is efficient for upcoming wireless communication systems for user selection and grouping and also improves the quality of service. In futures, the proposed deep learning model is enhanced with increased number of hidden layers. The implementation of deep learning with optimization may increase the system complexity, this issue will take into consideration for future and implements faster deep learning or deep reinforcement learning approaches.

References

[1]. Zhang, L.; Wu, Y.; Li, W.; Rong, B.; Salehian, K.; LaFleche, S.; Wang, X.; Park, S.I.; Kim, H.M.; Lee, J.-Y.; et al. Layered Division-Multiplexing for High Spectrum Efficiency and Service Flexibility in Next Generation ATSC 3.0 Broadcast System// IEEE Wirel. Commun. 2019, 26, 116–123

[2]. Ding, Z.; Liu, Y.; Choi, J.; Sun, Q.; Elkashlan, M.; Chih-Lin, I.; Poor, H.V. Application of Non-Orthogonal Multiple Access in LTE and 5G Networks// IEEE Commun. Mag. 2017, 55, 185–191.

[3]. Tseng, S.-M.; Kao, S.-C. User Selection Approach in Multiantenna Beam forming NOMA Video Communication Systems. Symmetry 2021, 13, 1737.

[4]. A. Masaracchia, D. B. Da Costa, T. Q. Duong, M. -N. Nguyen and M. T. Nguyen, "A PSO-Based Approach for User-Pairing Schemes in NOMA Systems: Theory and Applications," in IEEE Access, 2019, vol. 7, pp. 90550 - 90564.

[5]. Faeik T. Al Rabee& Richard D. Gitlin, Uplink Power-Domain Non-Orthogonal Multiple Access (NOMA): Bit Error Rate Performance With Channel Estimation Errors, International Journal of Interdisciplinary Telecommunications and Networking. IGI Global, 2020, vol. 12(4), pp. 65-73.

[6]. Kumaresan, S.P.; Tan, C.K.; Ng, Y.H. Deep Neural Network (DNN) for Efficient User Clustering and Power Allocation in Downlink Non-Orthogonal Multiple Access (NOMA) 5G Networks. Symmetry 2021, 13, 1507.

[7]. Kumaresan, S.P.; Tan, C.K.; Ng, Y.H. Efficient User Clustering Using a Low-Complexity Artificial Neural Network (ANN) for 5G NOMA Systems. IEEE Access 2020, 8, 179307–179316

[8]. Muhammad Hussain and Haroon Rasheed, “Nonorthogonal Multiple Access for Next-Generation Mobile Networks: A Technical Aspect for Research Direction”, Hindawi Wireless Communications and Mobile Computing Volume 2020, Article ID 8845371, 1-17.

[9]. Rajab, H.; Benkhelifa, F.; Cinkler, T. Analysis of Power Allocation for NOMA-Based D2D Communications Using GADIA. Information 2021, 12, 510.

[10]. Luo, J.; Tang, J.; So, D.K.; Chen, G.; Cumanan, K.; Chambers, J.A. A deep learning-based approach to power minimization in multi-carrier NOMA with SWIPT. IEEE Access 2019, 7, 17450–17460.

[11]. Aamina Akbar, Sobia Jangsher, Farrukh A. Bhatti, NOMA and 5G emerging technologies: A survey on issues and solution techniques, Computer Networks, Volume 190, 2021, 107950,

[12]. Yahya, Hamad; ahmed, ashfaq; Alsusa, Emad; Al-Dweik, Arafat (2022): Error Rate Analysis of NOMA: Principles, Survey and Future Directions. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.18975011.v1

[13]. Kumaresan, S.P.; Tan, C.K.; Lee, C.K.; Ng, Y.H. Low-complexity particle swarm optimization based adaptive user clustering for downlink non-orthogonal multiple access deployed for 5G systems. World Rev. Sci. Technol. Sustain. Dev. 2020, 1, 1

[14]. Lin, C.; Chang, Q.; Xianxu, L. A Deep Learning Approach for MIMO-NOMA Downlink Signal Detection. Sensors 2019, 19, 2526

[15]. Pan, J.; Ye, N.; Wang, A.; Li, X. A Deep Learning-Aided Detection Method for FTN-Based NOMA. Wirel. Commun. Mob. Comput. 2020, 2020, 5684851.

[16]. Yang, N.; Zhang, H.; Long, K.; Hsieh, H.Y.; Liu, J. Deep neural network for resource management in NOMA networks. IEEE Trans. Veh. Technol. 2020, 69, 876–886

[17]. Tseng, S.-M.; Chen, Y.-F.; Fang, H.-H. Cross PHY/APP layer user grouping and power allocation for uplink multi-antenna NOMA video communication systems. IEEE Syst. J. 2020, 14, 3351–3359

[18]. R. Sharkawy, K. Ibrahim, M. M. A. Salama, and R. Bartnikas, ‘‘Particle swarm optimization feature selection for the classification of conducting particles in transformer oil,’’ IEEE Trans. Dielectr. Electr. Insul., 2011, vol. 18, no. 6, pp. 1897–1907,

[19]. Simeone, O. A Very Brief Introduction to Machine Learning with Applications to Communication Systems. IEEE Trans. Cogn. Commun. Netw. 2018, 4, 648–664.