International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 12 Dec 2021, pp: 879-891 www.ijaem.net ISSN: 2395-5252

Deep Learning Based Sum Datarate and Energy Efficiency Optimization

S R Vidhya, T Jayasree

Lecturer, ECE Department Kamaraj Polytechnic College, Nagercoil,
Assistant Professor, ECE Department,Government College of Engineering, Tirunelveli,

Submitted: 01-12-2021 Revised: 12-12-2021 Accepted: 15-12-2021

ABSTRACT

The increasing demands for massive connectivity, low latency, and high reliability of future communication networks require new techniques. Multiple-input-multiple-output non-orthogonal multiple access (MIMO-NOMA), which incorporates the NOMA concept into MIMO, is an appealing technology to enhance system throughput and energy efficiency. However, rapidly changing channel conditions and extremely complex spatial structure degrade the system performance and hinder its application. Thus, to tackle these limitations, in this paper, we propose a deep learning-based MIMO-NOMA framework for maximizing the sum data rate and energy efficiency. Thanks to the impressive representation ability of the deep learning technique, the deep learning framework addresses the power allocation problem for achieving higher data rate and energy efficiency of MIMO-NOMA with the aid of training algorithms. Additionally, simulation results corroborate that the proposed deep learning framework is a good candidate to enhance the performance of MIMO-NOMA in term of power allocation, and extensive simulations show that it realizes larger sum data rate and energy efficiency compared with conventional strategies.

I. INTRODUCTION

1.1 INTRODUCTION TO 5G TECHNOLOGY

5G networks are digital cellular networks, for which the service area is divided into small geographical cells. The 5G wireless devices in a cell communicate by radio waves with a local antenna array and low power automated transceiver (transmitter and receiver) in the cell, over frequency channels assigned by the transceiver from a pool of frequencies that are reused in other cells. The local antennas are connected to transmission electronics connected to switching centers in the telephone network and routers for Internet access by high-bandwidth optical fiber or wireless backhaul connections. As in other cell networks, a mobile device moving from one cell to another is automatically handed off seamlessly to the current cell. 5G can support up to a million devices per square kilometer, while 4G supports only one tenth of that capacity. The new 5G wireless devices also have 4G LTE capability, as the new networks use 4G for initially establishing the connection with the cell, as well as in locations where 5G access is not available.

Several network operators use millimeter waves for additional capacity, as well as higher throughput.Millimeter waves have a shorter range than microwaves, therefore the cells are limited to a smaller size. Millimeter waves also have more trouble passing through building walls.Millimeter wave antennas are smaller than the large antennas used in previous cellular networks. Some are only a few centimeters long.

Massive MIMO (multiple-input multiple-output) was deployed in 4G as early as 2016 and typically used 32 to 128 small antennas at each cell. In the right frequencies and configuration, it can increase performance from 4 to 10 times. Multiple bitstreams of data are transmitted simultaneously. In a technique called beamforming, the base station computer will continuously calculate the best route for radio waves to reach each wireless device and will organize multiple antennas to work together as phased arrays to create beams of millimeter waves to reach the device.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 12 Dec 2021, pp: 879-891 www.ijaem.net ISSN: 2395-5252

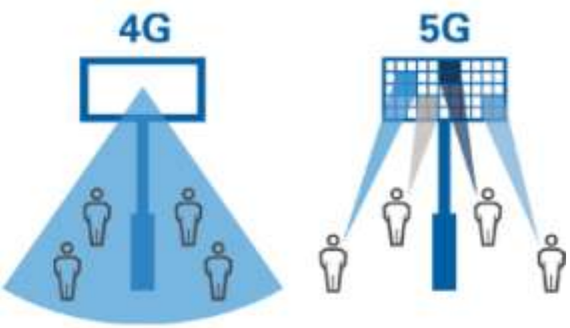

FIGURE: 1.1 4G AND 5G

1.2 MIMO TECHNOLOGY

A channel may be affected by fading and this will impact the signal to noise ratio. In turn this will impact the error rate, assuming digital data is being transmitted. The principle of diversity is to provide the receiver with multiple versions of the same signal. If these can be made to be affected in different ways by the signal path, the probability that they will all be affected at the same time is considerably reduced. Accordingly, diversity helps to stabilise a link and improves performance, reducing error rate.Several different diversity modes are available and provide a number of advantages:

- **Time diversity:** Using time diversity, a message may be transmitted at different times, e.g. using different timeslots and channel coding.
- **Frequency diversity:** This form of diversity uses different frequencies. It may be in the form of using different channels, or technologies such as spread spectrum / OFDM.
- **Space diversity:** Space diversity used in the broadest sense of the definition is used as the basis for MIMO. It uses antennas located in different positions to take advantage of the different radio paths that exist in a typical terrestrial environment.

MIMO is effectively a radio antenna technology as it uses multiple antennas at the transmitter and receiver to enable a variety of signal paths to carry the data, choosing separate paths for each antenna to enable multiple signal paths to be used.

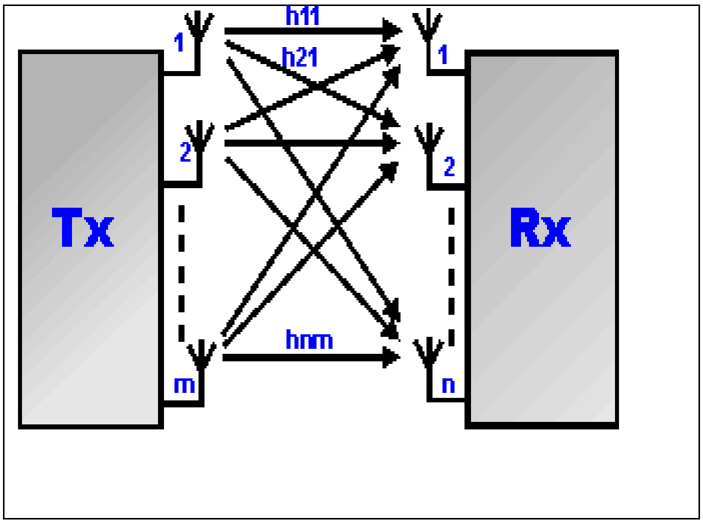

Figure 1. 2:General outline of MIMO system

1.3 NON ORTHOGONAL MULTIPLE ACCESS

Non-orthogonal multiple access (NOMA) is one of the most promising radio access techniques in next-generation wireless communications. Compared to orthogonal frequency division multiple access (OFDMA), which is the current de facto standard orthogonal multiple access (OMA) technique, NOMA offers a set of desirable potential benefits, such as enhanced spectrum efficiency, reduced latency with high reliability, and massive connectivity. The baseline

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 12 Dec 2021, pp: 879-891 www.ijaem.net ISSN: 2395-5252

idea of NOMA is to serve multiple users using the same resource in terms of time, frequency, and space.

The available NOMA techniques can broadly be divided into two major categories, i.e., power-domain NOMA and code-domain NOMA. Code-domain NOMA can further be classified into several multiple access techniques that rely on low-density spreading and sparse code multiple access. Other closely related multiple access schemes in this context are lattice-partition multiple access, multi-user shared access, and pattern-division multiple access.

Recent studies demonstrate that NOMA has the potential to be applied in various fifth generation (5G) communication scenarios, including Machine-to-Machine (M2M) communications and the Internet-of-Things (IoT).

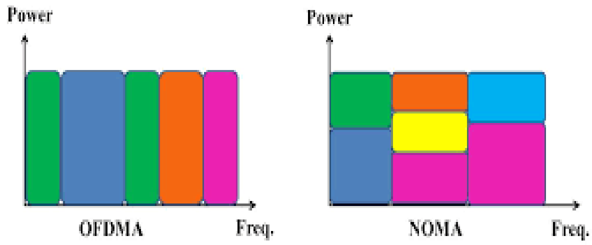

FIGURE 1.3 OFDMA AND NOMA COMPARISON

1.4 DEEP LEARNING BASED MIMO NOMA SYSTEMS

NON-ORTHOGONALmultiple access (NOMA) has been considered as an alternative technique to enhance spectrum efficiency for the future 5th generation (5G) networks and attracted a great interest within both academia and industry. Different from the traditional orthogonal multiple access (OMA) technology, NOMA is capable of concurrently serving multiple users in a single resource block with different power levels by a common base station (BS) [4]. By designing successive interference cancellation (SIC) at the receiver, NOMA can suppress co-channel interference and intra-cluster interference efficiently.

Besides, to schedule the transmission of signals over the same transmission period and bandwidth, superposition coding (SC) is adopted in NOMA systems. In the past few years, a number of researchers have been devoted to boosting the performance of NOMA systems. In [6], the authors carefully explored the performance of a downlink NOMA scheme with randomly deployed users. Then, [7] developed a NOMA unicast-multicast system that leads to a diversity order of NOMA equal to the number of multicast users. In order to improve the ergodic capacity for each user, a fair NOMA approach was proposed in the case of pairing a near base-station user and a cell-edge user.

II. LITERATURE SURVEY

The joint user and beam scheduling problem in beam-based massive multiple-input multiple-output (MIMO) systems is formulated based on the Lyapunov-drift optimization framework and the optimal scheduling policy is given in a closed-form. To address the weighted sum rate maximization problem (mixed integer programming) arisen in the Lyapunov-drift maximization, an algorithm based on the block coordinated update is proposed and proved to converge to the global optimum of the relaxed convex problem. In order to make the scheduling decisions based only upon statistical channel state information (CSI), asymptotic expressions of the downlink broadcast channel capacity are derived. Simulation results based on widely-adopted spatial channel models are given, which show that the proposed scheme is close to the optimal scheduling scheme, and outperforms the state-of-the-art beam selection schemes.

Vehicular ad hoc networks (VANETs) have been widely studied as an effective method for providing wireless communication connectivity in vehicular transportation systems. In particular, vehicular cloud systems (VCSs) have received abundant interest for the ability to offer a variety of vehicle information services. The data dissemination problem of providing reliable data delivery services from a cloud data center to vehicles through roadside wireless access points (APs) with local data storage.

Due to intermittent wireless connectivity and the limited data storage size of roadside

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 12 Dec 2021, pp: 879-891 www.ijaem.net ISSN: 2395-5252

wireless APs, the question of how to use the limited resources of the wireless APs is one of the most pressing issues affecting data dissemination efficiency in VCSs. We devise a vehicle route-based data prefetching scheme, which maximizes data dissemination success probability in an average sense when the size of local data storage is limited and wireless connectivity is stochastically unknown. We propose a greedy algorithm and an online learning algorithm for deterministic and stochastic cases, respectively, to decide how to prefetch a set of data of interest from a data center to roadside wireless APs.

Dimensionality loss is defined as the channel estimation overhead, which results in a loss of time-frequency resources in pilot-assisted wireless systems. In this project, the scaling result of dimensionality loss, i.e., the scaling factor, in frequency-division-duplex (FDD) massive multiple-input-multiple-output(MIMO) downlinks is derived. The scaling factor determines the amount of channel estimation overhead, and thus is vital to understand the downlink throughput in FDD massive MIMO systems. Moreover, the transmit diversity of the downlink channel is also derived. In the simulations, we adopt a geometry-based stochastic channel model to validate our analysis.

III. SYSTEM ANALYSIS

3.1 Existing System

Recently, unmanned aircraft systems (UASs) have attracted attention as a new avenue for commercial services. Using the flexible mobility of unmanned aircrafts (UAs), commercial services can be operated in wide areas.

However, thereis a problem in the wireless communication between the UAand its ground station. When several UASs are operated withinthe neighboring airspace, wireless-communication conflicts occur.One of the most effective solutions for this issue is to decide thecommunication schedule using a time-division multiple access(TDMA) scheme.

Furthermore, by spatially reusing the timeslot, numerous UAs can be operated within the neighboringairspace, in a limited frequency band. In this project, an efficient time-slot allocation for enhancing the frequencyresource utilization. Determines the timeslot allocation considering the time-slot spatial reuse, using avirtual cell-based space partitioning method.

In addition, weconsider the influence of the UA mobility on the network to decidethe parameters for the proposed resource allocation system

3.2 Block Diagram

The following figure represents the block diagram of a an existing system,in which an efficient time slot allocation is used.

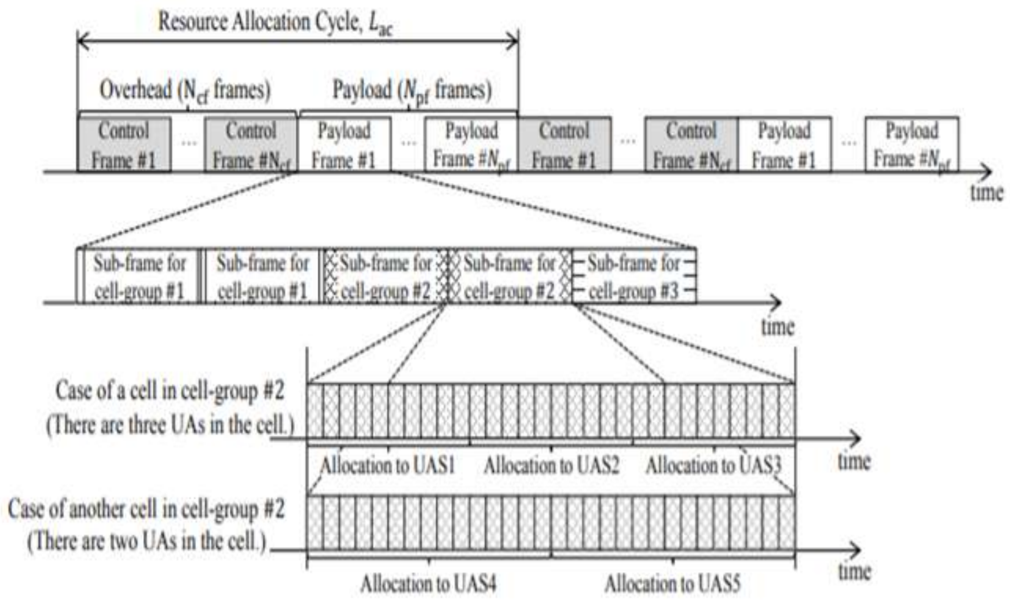

Fig. 3.1 Block Diagram of Existing System

3.3 Working Principle

A virtual cell-based resource allocation method for efficient frequency utilization for UASs. In spatial reuse of the time-slots is decided, based on a virtual cell-based network topology.In order to decide the set of UAs that can

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 12 Dec 2021, pp: 879-891 www.ijaem.net ISSN: 2395-5252

communicate simultaneously, we use a virtual cell-based space partitioning method. In numerous virtual cells having the same radius, r, are located over the coverage area of the resource allocation station. Each UA and its ground station are in a virtual cell. Here, the UA and its ground station are not necessarily located in the same virtual cell. The resource allocation for each UAS is decided such that packet drops, caused by interference from the other UAs, do not occur, even if the UA distribution is not uniform.

Hence, the time-slot allocation and radius of the virtual cell should be decided, when the SIRs of all the UASs satisfy the requirement.Generally, the value of the cell-group is determined based on the performance of wireless modules, such as the required length of the guard-time between timeslots. Therefore, we suppose the number of the cell-group as the given valueEach superframe consists of control and payload frames, i.e., the sum of the lengths of the control and payload frames is equal to the length of the superframe. During the control frames, the time-slot allocations are informed by the resource allocation station to the UASs.

3.4 Proposed System

Researchers designed a deep learning based traffic load prediction algorithm to forecast future traffic load and congestion by realizing better channel assignment. Additionally, unmanned aircraft systems (UASs) are regarded as an alternative solution for ground stations and unmanned aircrafts (UAs) in mobility scenarios but the resource allocation issue degrades their performance, and deep learning is regarded as a solution to overcome this problem. Thus, it is of great significance to apply deep learning in MIMO-NOMA systems for optimizing the power allocation issue.

In this work, for the sake of optimizing the sum data rate and the energy efficiency of MIMO-NOMA system, this work carries out a comprehensive research and provides a deep learning based framework.

User k signal is detected first the the unwanted noise signals are suppressed in the Non Orthogonal Multiple Access model –Successive Interference Cancellationn model.

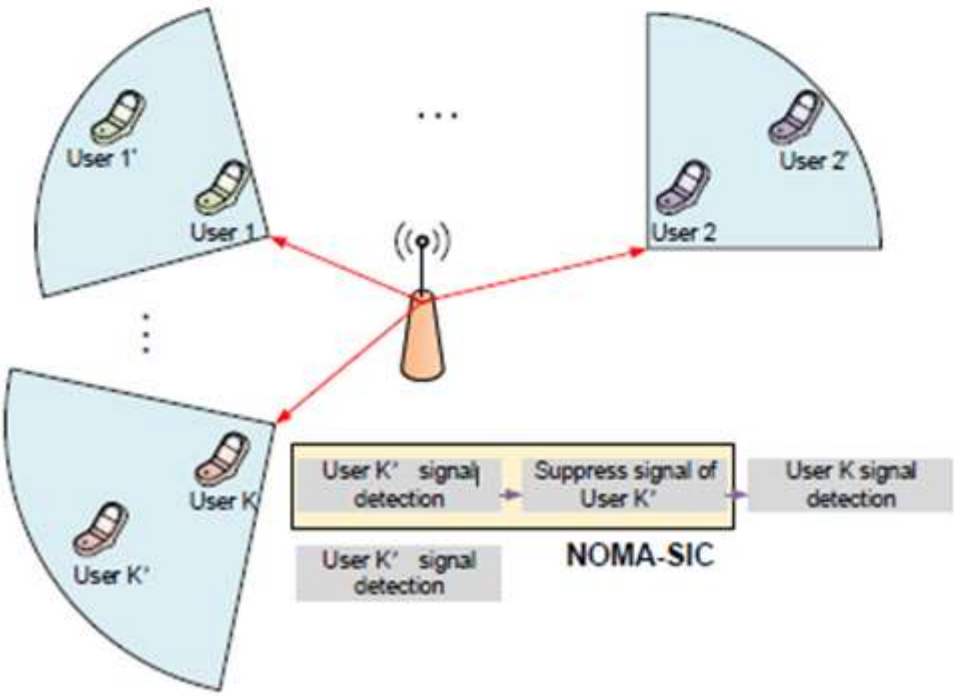

Fig 3.2 MIMO-NOMA system with multiple clusters

• To the best of our knowledge, this work first attempts to merge the state-of-the-art deep learning with MIMO-NOMA systems to realize better power allocation performance for sum data rate and energy efficiency optimization. Here, the whole MIMO -NOMA system is regarded as a black box and the proposed framework realizes end-to-end performance optimization. Thanks to deep learning, the proposed deep learning-based scheme is able to fully leverage the sparsity statistics and realize high-resolution channel estimation with the aid of the novel learning mechanism.

3.6 MIMO -Multiple Input Multiple Output formats:

MIMO is effectively a radio antenna technology as it uses multiple antennas at the transmitter and receiver to enable a variety of signal paths to carry the data, choosing separate paths for each antenna to enable multiple signal paths to be used. One of the core ideas behind MIMO wireless systems space-time signal processing in which time (the natural dimension of digital communication data) is complemented with the spatial dimension inherent in the use of multiple spatially distributed antennas, i.e. the use of multiple antennas located at different points. Accordingly MIMO wireless systems can be viewed as a logical extension to the smart antennas that have been used for many years to improve wireless.

It is found between a transmitter and a receiver, the signal can take many paths. Additionally by moving the antennas even a small distance the paths used will change. The variety of paths available occurs as a result of the number of objects that appear to the side or even in the direct path between the transmitter and receiver. Previously these multiple paths only served to introduce interference. By using MIMO, these additional paths can be used to advantage. They can be used to provide additional robustness to the radio link by improving the signal to noise ratio, or by increasing the link data capacity.

The two main formats for MIMO are given below:

Spatial diversity: Spatial diversity used in this narrower sense often refers to transmit and receive diversity. These two methodologies are used to provide improvements in the signal to noise ratio and they are characterised by improving the reliability of the system with respect to the various forms of fading.

Spatial multiplexing : This form of MIMO is used to provide additional data capacity by utilising the different paths to carry additional traffic, i.e. increasing the data throughput capability.

As a result of the use multiple antennas, MIMO wireless technology is able to considerably increase the capacity of a given channel while still obeying Shannon's law. By increasing the number of receive and transmit antennas it is possible to linearly increase the throughput of the channel with every pair of antennas added to the system. This makes MIMO wireless technology one of the most important wireless techniques to be employed in recent years. As spectral bandwidth is becoming an ever more valuable commodity for radio communications systems, techniques are needed to use the available bandwidth more effectively. MIMO wireless technology is one of these techniques.

ADVANTAGE:

- It maximize the sum rate performance of the proposed model
- It is based on statistical CSI, the frequency of executing the algorithm is significantly reduced, making it more preferable in practice.

3.7 Framework

We merge the Deep Learning Framework with the MIMONOMA system and derive an end-to-end approach for sum data rate and energy efficiency optimization. To boost the endto- end performance, we design a novel Deep Learning Framework carefully to approximate the power allocation optimization problem of the MIMO-NOMA system, and the Deep Learning Framework is implemented at the BS. After training the Deep Learning Framework, the BS will allocate a different power to each user. Though we do not design “physical users” in the Deep Learning Framework, the features of the channel links and the users have been extracted as training examples.

In this way, information of all the users and channel conditions are included in the training examples. Then, in order to improve the system performance, an effective learning method is provided to train the Deep Learning Framework. Furthermore, on the basis of the deep learning-based framework, superior algorithms are proposed for improving the sum data rate and for enhancing the energy efficiency in the MIMO-NOMA system. Here we are taking the estimated results of the CDNN framework, we are using this value as the maximum iteration value.

The following pictures depicts the model output for a Convolutional Deep Neural Network in which the neurons are interconnected with one another, these interconnected neurons work as a human brain when trained it produces output by prediction. Here the framework acts a precoder which is used for to improce the directivity of the signals as we are using MIMO system.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 12 Dec 2021, pp: 879-891 www.ijaem.net ISSN: 2395-5252

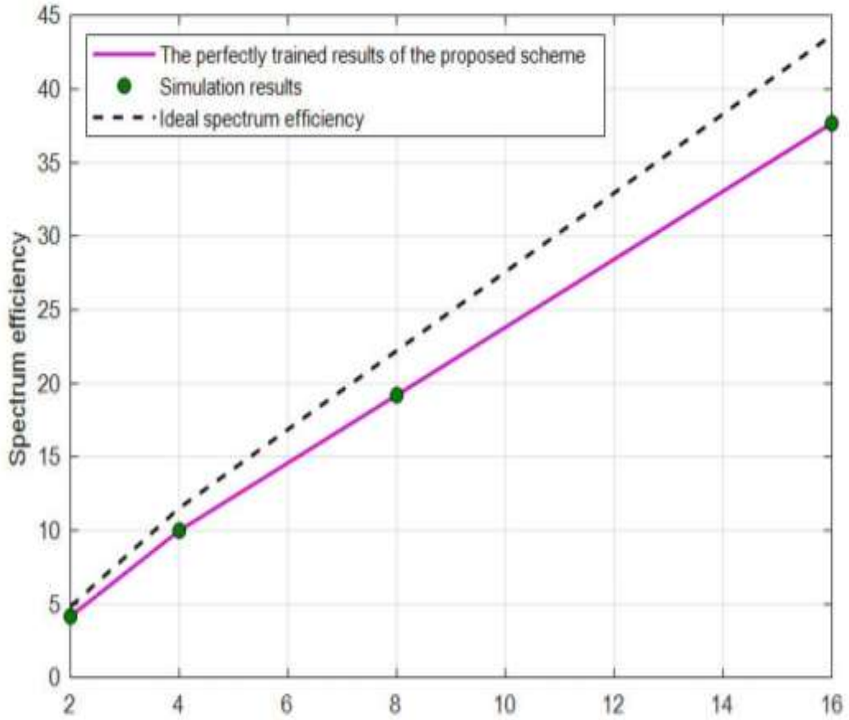

Figure 3.3:model output for energy efficiency against number of clusters m of CDNN framework

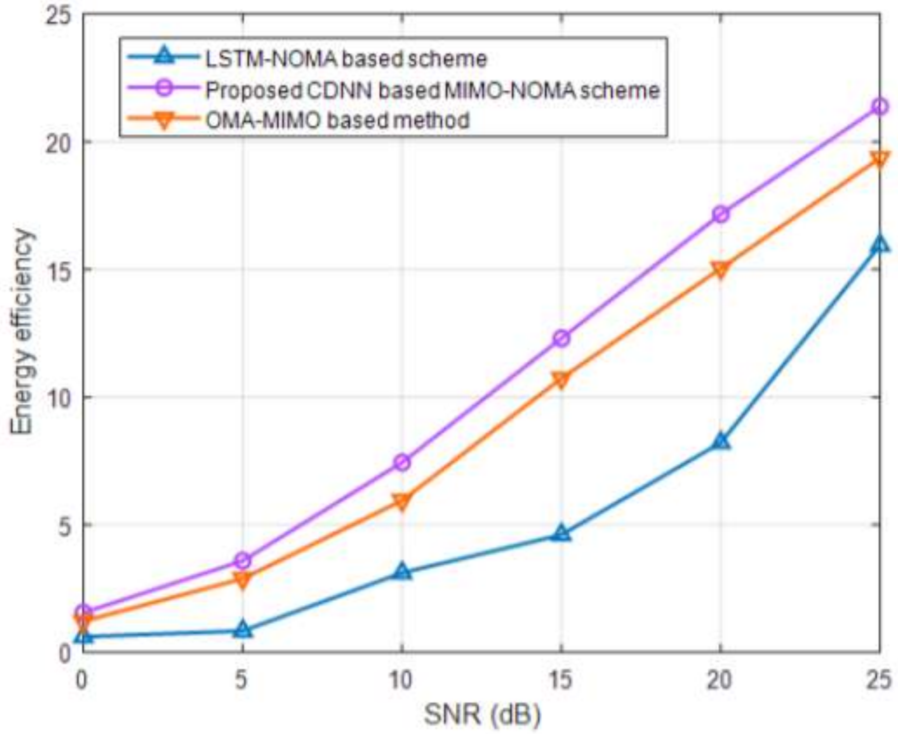

Figure 3.4:Energy efficiency in various methods

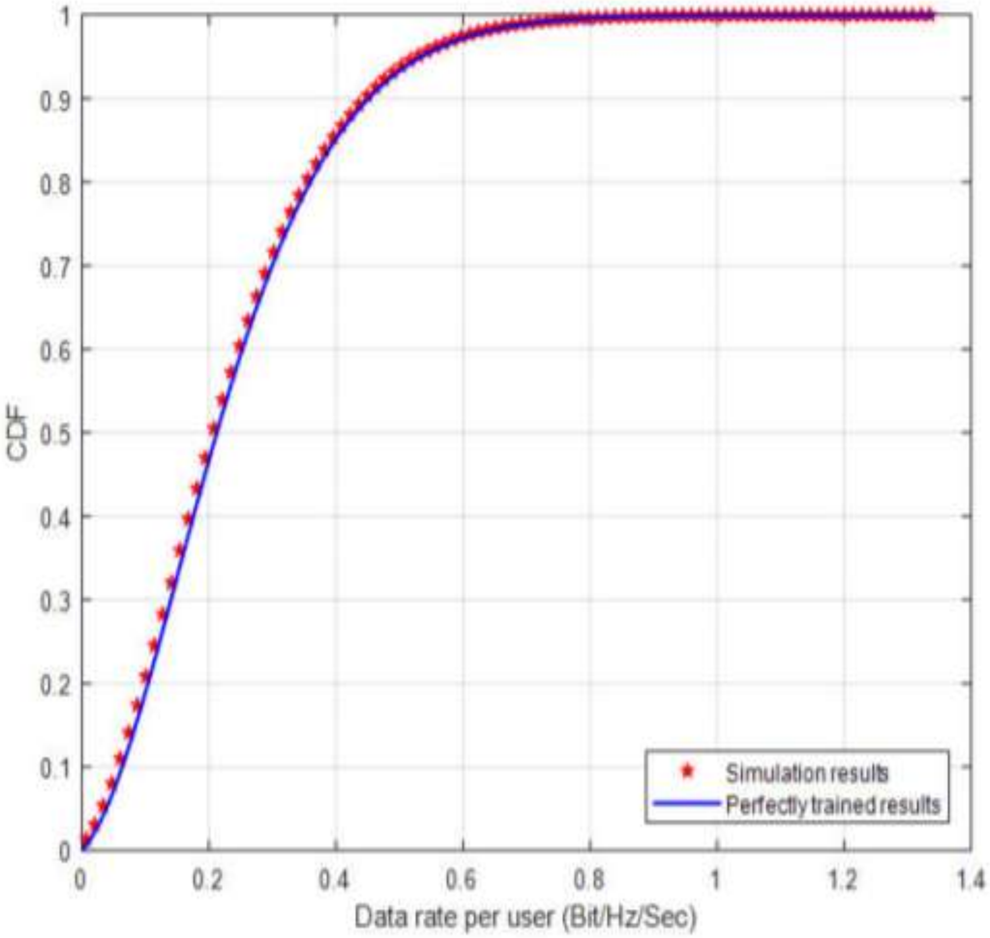

Figure 3.5:data rate per user

Fig. 3.5 Depicts the sum data rate versus SNR with various lengths of training sequences and different batch sizes, where L = 16 bits, L = 8 bits, 1000 batch sizes, and 500 batch sizes are considered. It can be observed from Fig. 3 that the sum data rate is enhanced as the SNR increases. This output is taken as a maximum iteration value in our project hence we get an efficiency equal to the output from CDNN framework, with a Matlab program, thus our project proves that it is user friendly and cost efficient with an efficient data rate output

IV. RESULTS FOR SIMULATION

4.1 Results

Here we have the Cumulative distribution Function(CDF) of data rate per user, here we compare the CDF based on two models, the dotted lines represents our proposed model here power are allocated according to the need and location of the user whereas the line represents other model in which same or equal power are distributed to the users irrespective of their locations.here SE per UE represents the signal received per user equipment.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 12 Dec 2021, pp: 879-891 www.ijaem.net ISSN: 2395-5252

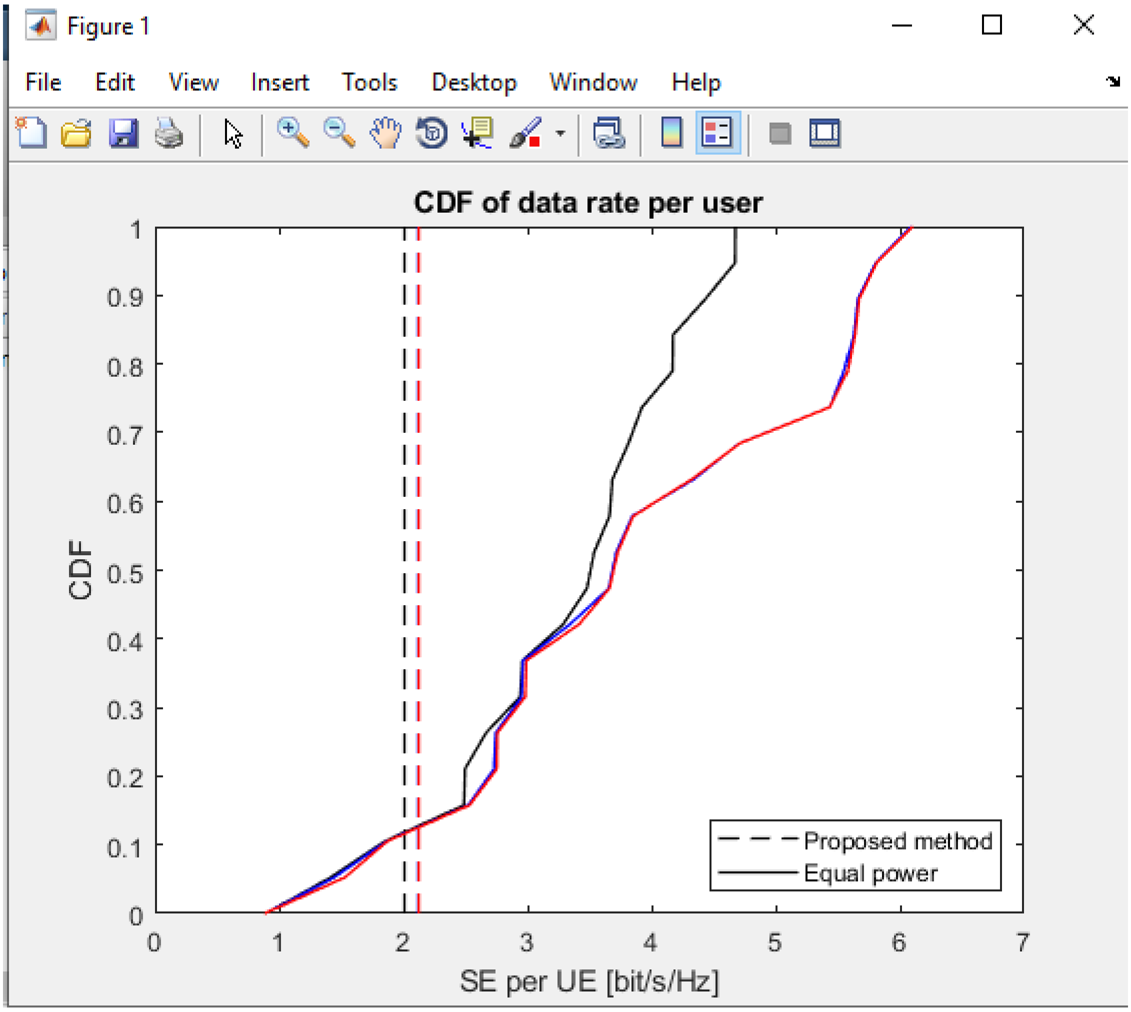

Fig no 5.1 CDF of data per user

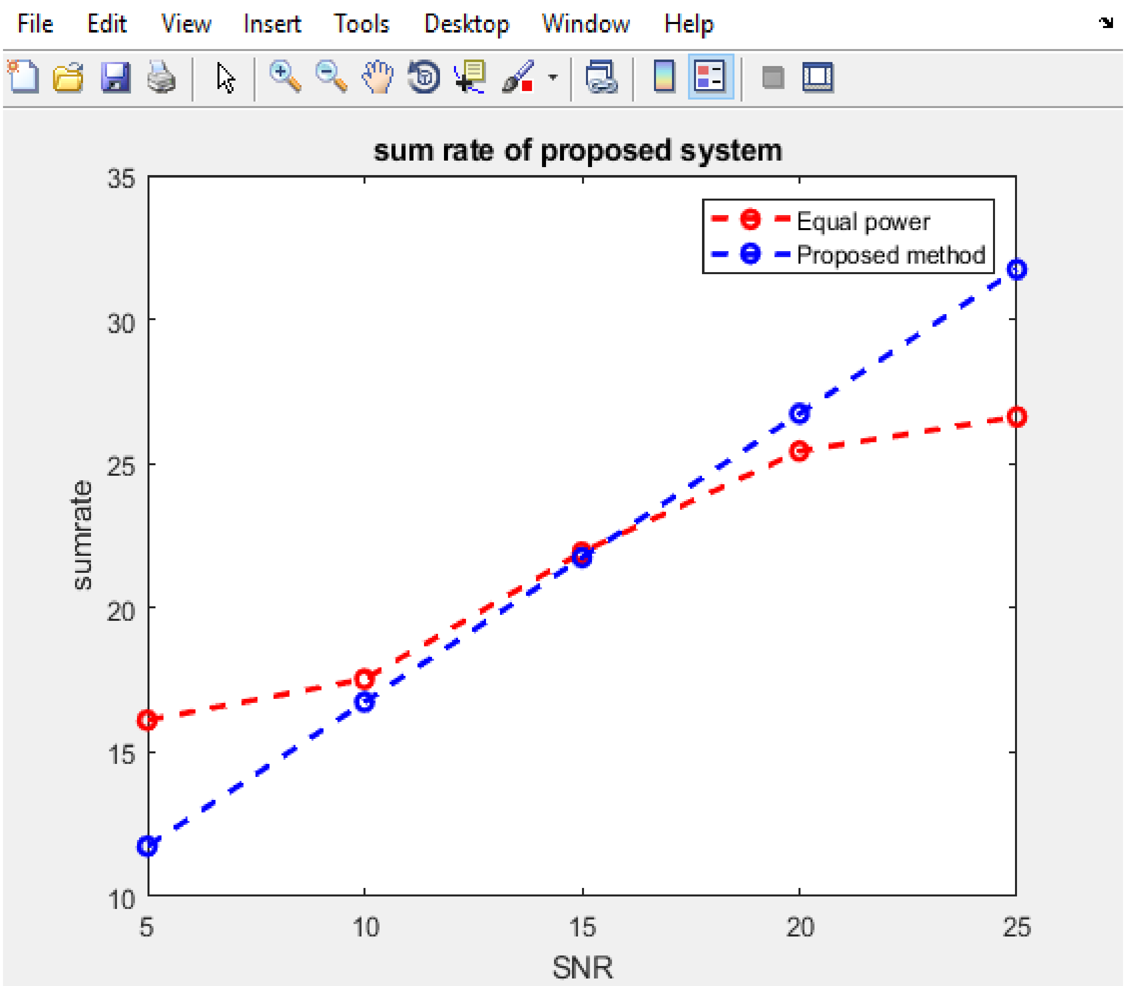

Fig no 5.2 Sum data rate of proposed system

In the above picture the red dotted lines represents the sum datarate in a model with equal power distribution. The blue dotted line represents the sum data rate in a model with conditioned power distribution.

The increase in sum data rate improves the system efficiency. The efficiency of our proposed system and system with equal power distribution is represented in the below output figure. Red dotted line shows the energy efficiency of system with equal power allocation and blue dotted line shows the energy efficiency of the system with conditioned power distribution. Thus our model proves to the best in comparison with the existing model.

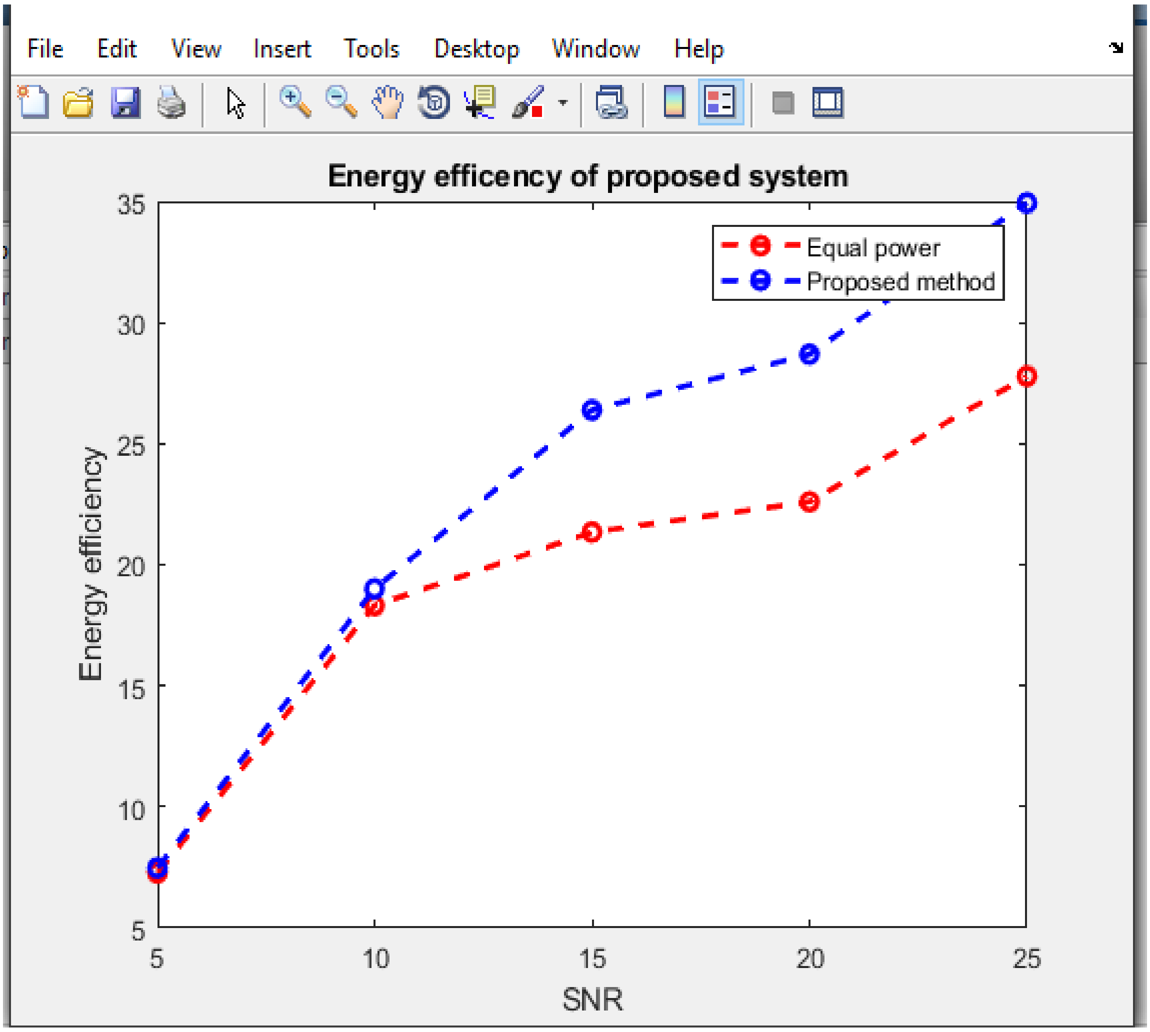

Fig no 5.3 Energy efficiency of proposed system

Both energy efficiency and sum data rate are plotted with respect to Signal To Noise ratio(SNR). Thus the sum data rate and the energy efficiency is achieved in our proposed Deep Learning based MIMO-NOMA Systems.

V. CONCLUSION AND FUTURE SCOPE

5.1 CONCLUSION

In this paper, by integrating the deep learning into the MIMO-NOMA system, we have proposed a deep learningbased scheme for optimizing the power allocation based on the developed DNN. Here, after formulating the power allocation problem, we designed a super deep learning framework where specific activation functions are implemented at each layer. Then, novel learning methods were provided to extract important spatial features of the MIMO-NOMA and train the proposed deep learning framework which can be divided into offline learning and online learning states.

The impressive representation and mapping capacities of the deep learning enable the complicated MIMO system to attain accurate CSI and achieve better SIC performance at the users, and power allocation optimization problem was addressed with the aid of the approximation ability of the deep learning framework. Furthermore, simulation results were presented and the superior performance of the deep learning framework-based MIMO-NOMA framework was verified, and we also tested the robustness of the deep learning framework .

5.1.1 FUTURE SCOPE:

In the future, this work will be extended to the **time-varying fadingscenarios**, in which the power allocation needs to follow the instantaneous fading conditions. Also, we will attempt to introduce the emerging **cognitive radio** networks to the proposed deep learning-based MIMO NOMA system and further optimize the MIMO-NOMA systems. Besides, our attention will be drawn on **security and system capacity** issues.

REFERENCE

[1]. Y. Saito, A. Benjebbour, Y. Kishiyama, and T. Nakamura, "System level performance evaluation of downlink non-orthogonal multiple access (NOMA)," in Proc. IEEE Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC), London, U.K., Sep. 2013, pp. 611–615.

[2]. Z. Ding et al., "Application of non-orthogonal multiple access in LTE and 5G networks," IEEE Commun. Mag., vol. 55, no. 2, pp. 185–191, Feb. 2017.

[3]. H. Huang, J. Xiong, J. Yang, G. Gui, and H. Sari, "Rate region analysis in a full-duplex-aided cooperative nonorthogonal multiple-access system," IEEE Access, vol. 5, pp. 17869-17880, Aug. 2017.

[4]. M. Zeng, A. Yadav, O. A. Dobre, G. I. Tsiropoulos, and H. V. Poor, "Capacity comparison between MIMO-NOMA and MIMO-OMA with multiple users in a cluster," IEEE J. Sel. Areas Commun., vol. 35, no. 10, pp. 2413-2424, Oct. 2017.

[5]. S. Timotheou and I. Krikidis, "Fairness for non-orthogonal multiple access in 5G systems," IEEE Signal Process. Lett., vol. 22, no. 10, pp. 1647–1651, Oct. 2015.

[6]. Z. Ding, Z. Yang, P. Fan, and H. V. Poor, "On the performance of nonorthogonal multiple access in 5G systems with randomly deployed users," IEEE Signal Process. Lett., vol. 21, no. 12, pp. 1501–1505, Dec.2014.

[7]. L. Yang, J. Chen, Q. Ni, J. Shi, and X. Xue, "NOMA-enabled cooperative unicast-multicast: Design and outage analysis," IEEE Trans. Wireless Commun., vol. 16, no. 12, pp. 7870-7889. Dec. 2017.

[8]. J. A. Oviedo and H. R. Sadjadpour, "A fair power allocation approach to NOMA in multiuser SISO systems," IEEE Trans. Veh. Technol., vol. 66, no. 9, pp. 7974-7985, Sep. 2017.[9] J. G. Andrews et al., "What will 5G be?" IEEE J. Sel. Areas Commun.,vol. 32, no. 6, pp. 1065–1082, Jun. 2014.

[9]. C. L. I, C. Rowell, S. Han, Z. Xu, G. Li and Z. Pan, "Toward green and soft: A 5G perspective," IEEE Commun. Mag., vol. 52, no. 2, pp. 66-73, Feb. 2014.

[10]. J. Hoydis, S. ten Brink, and M. Debbah, "Massive MIMO in the UL/DLof Cellular Networks: How Many Antennas Do We Need?," IEEE J. Sel.Areas Commun., vol. 31, no. 2, pp. 160-171, Feb. 2013.

[11]. T. L. Marzetta, "Noncooperative cellular wireless with unlimited numbersof base station antennas," IEEE Trans. Wireless Commun., vol. 9, no. 11, pp. 3590-3600, Nov. 2010.

[12]. Z. Ding, F. Adachi, and H. V. Poor, "The application of MIMO to nonorthogonal multiple access," IEEE Trans. Wireless Commun., vol. 15, no. 1, pp. 537-552, Jan. 2016.

[13]. Z. Ding, R. Schober, and H. V. Poor, "A general MIMO framework for NOMA downlink and uplink transmission based on signal alignment," IEEE Trans. Wireless Commun., vol. 15, no. 6, pp. 4438-4454, Jun. 2016.

[14]. Y. Chi, L. Liu, G. Song, C. Yuen, Y. L. Guan, and Y. Li, "Practical MIMO-NOMA: Low complexity & capacity-approaching solution," IEEE Trans. Wireless Commun., vol. 17, no. 9, pp. 6251-6264, Sep. 2018.

[15]. B.Wang, L. Dai, Z.Wang, N. Ge, and S. Zhou, "Spectrum and energy efficient beamspace MIMO-NOMA for millimeter-wave communications using lens antenna array," IEEE J. Sel. Areas Commun., vol. 35, no. 10, pp. 2370-2382, Oct. 2017.

[16]. W. Shin, M. Vaezi, B. Lee, D. J. Love, J. Lee, and H. V. Poor, "Coordinated beamforming for multi-cell MIMO-NOMA," IEEE Commun.Lett., vol. 21, no. 1, pp. 84-87, Jan. 2017.

[17]. H. Chiu and R. Gau, "Opportunistic matrix precoding for non-separable wireless MIMO-NOMA networks," in Proc. 2018 IEEE 87th Veh. Technol. Conf. (VTC Spring), Porto, Portugal, Jun. 2018, pp. 1-6.

[18]. H. Wang, R. Zhang, R. Song, and S. Leung, "A novel power minimization precoding scheme for MIMO-NOMA uplink systems," IEEE Commun. Lett., vol. 22, no. 5, pp. 1106-1109, May 2018.

[19]. Y. Liu, G. Pan, H. Zhang, and M. Song, "On the capacity comparison between MIMO-NOMA and MIMO-OMA," IEEE Access, vol. 4, no. 6,pp. 2123–2129, Jul. 2016.

[20]. K. Xiao, L. Gong, and M. Kadoch, "Opportunistic multicast NOMA with security concerns in a 5G massive MIMO system," IEEE Commun. Mag., vol. 56, no. 3, pp. 91-95, Mar. 2018.

[21]. D. Tweed and T. Le-Ngoc, “Dynamic resource allocation for uplink MIMO NOMA VWN with imperfect SIC,” in Proc. 2018 IEEE Int. Conf. Commun. (ICC), Kansas City, MO, USA, May 2018, pp. 1-6.

[22]. S. Ali, E. Hossain, and D. I. Kim, “Non-orthogonal multiple access (NOMA) for downlink multiuser MIMO systems: User clustering, beamforming, and power allocation,” IEEE Access, vol. 5, pp. 565-577, Dec. 2016.