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ENERGY-EFFICIENT RESOURCE ALLOCATION IN THE NOMA NETWORKS USING DEEP LEARNING ALGORITHMS

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ABSTRACT
The reliability and quality of services provided by communication technology are requirements for future communication systems. The reliability of communication systems depends on low latency, high data rates, and massive connectivity. The multiple input, multiple output, non-orthogonal multiple access approach fulfils the requirements of future communication systems such as 5G. The incorporation of MIMO-NOMA suddenly changing several factors such as channel condition and complex spectral structure decline the system efficiency and impede its application. Now the overcome the limitation of channel condition and resource allocation in NOMA employed deep learning algorithm. the proposed algorithm improves the energy efficiency and data rates of MIMO-NOMA model. The proposed algorithm uses convolutional neural network and firefly algorithm. the employed firefly algorithm removes the local interference and boost the feature map of convolutional layer. For the validation of the proposed algorithm, simulate in MATLAB environments with parameters of MIOM-NOMA. The results of the simulation compare with those of other existing deep learning algorithms such as recurrent neural networks, long-short term memory, and convolutional neural networks. The comparative results of the analysis suggest that the proposed algorithm is efficient in terms of power allocation and sum data rates.

Keywords: - MIMO-NOMA, Deep Learning, Power allocation, energy efficiency, Firefly algorithm

INTRODUCTION
The next generation of wireless communication demands reliability and quality of service. The reliability and quality of services depend on the management of resources in wireless communication. Resource management is the pivot point for energy efficiency and the spectral efficiency of wireless communication. the efficacy of the sum data rate, such as channel allocation, transmit power control, and user admission control. However, there are still some bottleneck issues with data transfer rate, computational efficiency, and network latency. Meanwhile, to improve data rate, capacity, and coverage of networks and energy efficiency, the non-orthogonal multiple access (NOMA) approach was universally adopted in wireless communication. Employing the NOMA approach for multiple users in the same subchannel, spectral efficiency and energy efficiency can be improved in wireless communication. Despite several approaches to resource allocation optimization in wireless communication, NOMA pointed in the direction of a new power domain dimension with a multiple access model. The power domain NOMA (PD-NOMA) is the primary key of 5G networks. PD-NOMA ensures that several users are served with the same resource by applying superposition coding (SC) methods at the transmitter and successive interference cancellation (SIC) at the receiver. The reported survey suggests that recently, several model-based resource allocation methods have been proposed to increase energy efficiency (EE) or spectral efficiency (SE) objectives in NOMA systems. [4] describes the power allocation and subchannel assignment problems. Some studies are based on machine learning algorithms for resource allocation and grouping of users. For the grouping of users and user equipment's several authors employ clustering algorithms such as K-means and affinity propagation clustering algorithms. The improved grouping of user clusters increases energy efficiency. The limitations of machine learning algorithms are overcome with deep learning algorithms, deep reinforcement learning, Q-learning, and many variants of machine learning algorithms. With readily available training inputs and outputs, deep learning has been used in some studies as a model-free and data-driven approach to reduce computational complexity. By first training the network offline with simulated data and then using the well-trained networks during the online process, [5] and [6] use neural networks to solve resource allocation problems. The training process is typically time-consuming, and it is frequently difficult to find the right data set or optimal

solutions. The search and optimization algorithms employed in subchannels for minimization of interference. The employed algorithms, such as Firefly and many others, employ meta-heuristic functions. Several meta-heuristic optimization algorithms are employed in the NOMA model for the allocation of power, such as particle swarm optimization, genetic algorithm, and the improved grey wolf optimization algorithm. This paper employed the Firefly algorithm for the removal of interference in the local subchannel. The Firefly algorithm is based on the behaviours of natural fireflies. The spectral efficiency (SE) and quality of services motivated me to work in the area of resource allocation and optimization of MIMO-NOMA. Recently, several authors have contributed more with the application of swarm intelligence and deep learning algorithms. This paper proposes advanced CNN networks for the optimization of data rate and power allocation to base stations. The proposed CNN algorithm followed the ReLU activation learning function and was combined with the Firefly algorithm for minimization of noise interference. In addition, the advantage of a deep learning scheme over a MIMO-NOMA is that it can be estimated to produce effective energy distribution for all users. However, other deep learning strategies like long-short term memory (LSTM), recurrent neural networks (RNN), and convolutional neural networks (CNN) In the proposed algorithm, a deep neural network was trained to find the best course of power distribution and improve the sum rate of data. The objective of this paper is to optimized resource allocation approach in the MIMO-NOMA model. This paper focuses on a comprehensive review of deep learning and other learning approaches employed in NOMA resource optimization. Now summarise the contributions of the paper, which are mentioned below.

1. A novel approach to merging the Firefly algorithm with CNN for MIMO-NOMA systems The proposed algorithm performs better power allocation and resource optimization.
2. The results of the proposed algorithm is compared with those of existing deep learning algorithms such as LSTM, RNN, and CNN.
3. Minimization of group interference and improves the power allocation at the base station.
4. The proposed algorithm improves sum data rates and efficiency of energy utilization.

The remaining paper is organised as follows: The recent work in the area of deep learning on NOMA resource optimization is discussed in Section II. In Section III, we describe the system model, problem formulation, deep learning, and proposed algorithm. In Section IV, we describe the simulation results of deep learning and proposed algorithms. Section V describes results and discussion and finally concludes in Section VI.

II. RELATED WORK

In this [1] authors proposed a framework for resource allocation and power optimization in non-orthogonal multiple access (NOMA). The proposed framework employed two algorithms, deep neural network and Lagrange dual decomposition algorithm. The employed approach resolves issues of subchannel and power allocation. The main achievements of this proposed algorithm are efficient energy optimization in manners of lower complexity. In this [2] authors improve the energy efficiency employing two-step deep reinforcement learning (DRL). The employed algorithm resolves issues of non-convex and dynamic optimization. The processing of algorithm acquired deep q network (DQN) and deep deterministic policy gradient (DDPG) networks for allocation of power for all users. The policy of reinforcement learning updated by the weight adjustment of neural networks. the employed algorithm enhances the performance of NOMA system model. in [3] authors proposed machine learning algorithm k-means clustering algorithm for separation of user problems and power optimization. The proposed algorithm employed on channel corelation process and increases convergence of NOMA-MIMO. The proposed algorithm only for Terahertz NOMA-MIMO networks. the employed algorithms also reduce computational overhead and energy efficiency of systems. In [4], the authors proposed a signature-based optimization algorithm for grant-free NOMA with random and nonuniform user activations. The signature-based optimization approach employs a deep neural network for the autoencoder transceiver. The proposed algorithm improves the efficiency of the NOMA system model. In [5], the authors explore features of Faster Than Nyquist (FTN) and nonorthogonal multiple access for signal transmission on the same physical resources. The joint approach to signal transmission increases user interference. To minimize and improve the detection process, the authors employed the deep learning method. The employed method improves detection accuracy and reduces the latency of the network. In [6], the authors propose a cascaded deep neural network-based framework for cooperative NOMA systems. The proposed system encapsulates a holistic optimization approach for entire NOMA systems. The authors design a multiple loss function to estimate BER performance for a multi-task-oriented training method to resolve the problem of end-to end training. The proposed algorithm also optimizes the process of power allocation. In [7], the authors proposed deep learning-based multi-user detection for uplink NOMA for massive communication. The proposed system performs joint channel estimation; however, channel state information is not required. The proposed system improves error performance in uplink NOMA instead of conventional detection and estimation processes such as channel state information (CSI). The proposed system integrates the Internet of Things for multiple device communication. In [8], the authors study the application of a deep learning algorithm to nonorthogonal multiple access performance. The employed deep learning algorithm improves the effectiveness and efficiency of NOMA systems. In order to achieve high-efficiency data transmission at a reasonable cost, further examine the integration of non-orthogonal communication and neural computation. Finally, from the perspectives of online reconfigurability and adaptability to the constantly changing environment of wireless communication. In [9], the authors proposed deep learning based joint channel estimation for OFDM-NOMA. The proposed channel estimation employs the Rayleigh fading channel model for the estimation of symbols at the receiver side. The proposed system does not require channel state information (CSI) for the insertion of the pilot symbol. The proposed system improves the performance of BER and interference instead of conventional successive interference canceler-based detection. In [10], the authors employed a deep neural network (DNN) for multi user detection. The employed deep neural network algorithm optimized the processes of channel estimation and data detection. The deep neural network algorithm improves the efficiency of NOMA systems and reduces the computational overhead of resource allocation. In [11], the authors proposed a deep learning-based NOMA detector for different channel conditions. The proposed system of detectors reduces interference and improves the performance of the system. The results of the proposed system compare with successive interference cancellation (SIC). The proposed system increases the performance of BER and clipping ratio (CR). In [12], the authors explore deep reinforcement learning (DRL) algorithms in NOMA for energy optimization. The employed DRL algorithms resolve the convex problem of non-linearity in channel estimation. The DRL algorithm adopts the Q-learning process and designs the policy of channel and power allocation. The employed policy of algorithms increases convergence speed and efficient energy utilization. In [13], the authors employed a deep neural network for the detection of active users (AUD) at the base station. The process of deep neural networks identifies the active users and finally detects active users in networks. The process of deep neural networks applies a multi-stage transfer learning method. The proposed methods improve the efficiency of NOMA resource allocation. In [14], the authors proposed a radio resource allocation approach for the management of traffic congestion. The proposed method is a combination of integrated backhaul networks and deep reinforcement learning. The proposed algorithm optimizes the policy of resource allocation for all user equipment. The applied algorithm optimized the allocation of power and improves the efficiency of resource management in the multiple access method. In [15], the authors proposed a user grouping algorithm based on the affinity propagation clustering algorithm. The employed algorithm groups the user's equipment based on correlation and distance factors. The proposed algorithm resolves the issue of non-convex problems and improves the process of power allocation. In [16], the authors explore the concept of a 5G communication model prototype and describe several challenges and limitations of the NOMA model. The limitation of resource allocation to cope with machine learning algorithms The machine learning algorithms employed improve the performance of 5G communication systems. In [17], authors explore resource optimization for the Internet of Things network. They employed a machine learning based k-means algorithm for grouping resources according to user requests. The proposed resource allocation algorithm is very efficient and improves the performance of IoT networks in rural and urban areas. In [18], the authors describe the hybrid approach of energy harvesting, cognitive radio, and NOMA for improvements in energy efficiency and spectral efficiency of net generation communication systems.

They employed deep reinforcement learning (DRL) methods for the management of multidimensional resources. The employed methods reduce packet losses and improve the efficiency of systems. In [19], the authors proposed a resource allocation method based on deep learning algorithms for SCMA. The proposed algorithm resolves the issue of automatic inter-cell interference. The proposed algorithm estimates the interference of the current subframe and minimize. The employed algorithm improves the performance of SCMA systems. In [20], the authors elaborate on resource optimization in cloud radio access networks. The authors take into account giving mobile users a coordinated allocation of radio and computing resources. It may be necessary to create complex, resource-intensive algorithms to allocate resources in the best way possible while still meeting the hybrid automatic repeat request deadline. They employed two integer linear programming (ILP) problems that implement a coordinated distribution of radio and computer resources with the goals of, respectively, maximising throughput and users' satisfaction. In [21], the authors address the joint optimization problem in reconfigurable intelligent surfaces (RIS) and NOMA for downlink transmission. The joint optimization problem reduces the sum data rate of transmission in NOMA networks. The process of optimization applies a deep deterministic policy gradient (DDPG) to control the phase shift of RIS. The proposed algorithm improves the performance of systems. In [22], the authors employed three machine learning algorithms for joint optimization problems. It employs algorithms such as long short-term memory (LSTM), deep Q-network, and clustering algorithms. The LSTM algorithm predicts the behaviour of mobile users. The deep Q-learning algorithm determines power allocation policy, and the clustering algorithm performs the task of grouping users. The employed process increases the gain of networks. In [23], the authors proposed deep learning and non- deep learning algorithms for the allocation of power in the MIMO-NOMA system. The energy efficient proposed algorithm is called EE-DNN and optimized the power allocation in multidimensional resource management. The proposed algorithm overcomes the complexity and latency of networks. In [24], the authors address the problem of user clustering in NOMA systems. The authors address problem solving using extreme machine learning (ELM) algorithms. The processing of the ELM algorithm is very fast compared to other artificial neural network algorithms. The employed algorithm performs optimal cluster formation based on user channel gain and powers. In [25], the authors address the problem of radio resource allocation in intelligent transportation systems (ITS). The adoption of a non-orthogonal multiple access approach in ITS reduces traffic congestion problems and improves the spectral efficiency of networks. In [28], the authors address the problem of the integration of different networks in the 5G communication system. The major problem in integration is resource allocation and the management of interference. The employed machine learning algorithm cannot overcome the limitations of resource assignments in 5G networks. In [29] authors address resource allocation and power control in satellite-IoT uplink systems. The authors employed a deep reinforcement learning algorithm for the policy determination of online resource allocation. The proposed algorithm reduces the gap between quality of service and resource efficiency. In [30], the authors address the problem of radio resource allocation management. The authors of the radio resource allocation employed supervised learning and reinforcement. The process of resource allocation is online as demand for traffic increases. The proposed system improves the spectral efficiency of systems. In [31], the authors address the problems of uncertainty in location information in millimetre wave in 5G communication systems. The uncertainty of location generates GPS errors. The distorted location of users increases the clustering problem in beam management. The authors employed a machine learning clustering algorithm for the minimization of grouping error. They also apply deep reinforcement learning (DRL) for resource allocation. The employed method of resource allocation improves the efficiency of the 5G millimetre wave. In [32], the authors implement a novel radio resource allocation scheme in ultra-low latency proactive vehicular networks to guarantee the reliability of downlink communication. They identify the success rate of data transmission as a reliable indicator, and propose a joint radio resource allocation model based on the generalized closed-loop, where the anchor node (AN) uses the radio resource utilization information (RRUI) from the vehicle in the most recent uplink as a guide to help resource allocation. In [33], the authors study resource allocation and management in 5G and beyond 5G communication systems. address the problems of power allocation, energy efficiency and apply machine learning algorithms for optimisation of resource allocation in 5G communication. In [34], the authors discuss the bottleneck issue of machine-to-machine communication in a cellular network. The resource of the cellular network is used by machine-to-machine communication; the traffic load of human based communication is increasing. The increased traffic degraded the performance of the communication system. The authors proposed a deep reinforcement learning algorithm to determine policy for the allocation of spectrum and power. The employed approach increases the efficiency of systems. In [35], the authors address the problems of a dynamic resource allocation approach in small scale networks. Poor resource allocation approaches maximise the error of estimation in NOMA. The employed algorithm minimizes the rate of errors and improves the resource allocation approach. In [37], authors address the imperfect successive interference cancellation (SIC) technology used by the NOMA system at the receivers, as well as the power allocation stage and the user scheduling stage, in relation to the resource management problem. The general fully connected DNN is trained to approximate the interior point method's (IPM) power allocation stage, which not only significantly boosts computational efficiency but also raises the sum rate of the system. In [38], the authors proposed a decentralized DRL framework for the optimization of power allocation. The deep deterministic policy gradient (DDPG) algorithm is used to learn policy for the allocation of power. The applied algorithm improves the efficiency of energy in NOMA systems. In [39], the authors propose a learning technique that recognizes the original transmit sequences by automatically analysing the channel state information (CSI) of the communication system. The proposed deep learning method can combine the channel estimation process with the recovery of the desired signal suffering from channel distortion and multiuser signal superposition. This is in contrast to existing SIC schemes, which must search for the optimal order of the channel gains and remove the signal with a higher power allocation factor while detecting a signal with a lower power allocation factor. In [40], authors proposed resource allocation methods based on deep reinforcement learning for optimal user direction. Also explore channel assignments and inter-cell interference management in NOMA networks. The employed approach increases the efficiency of NOMA systems.

III. METHODOLOGY

This section describes the system model of MIMO-NOMA and the problem formulation of energy efficiency and the minimization of energy factors in transmit signals. Also explore deep learning algorithms, firefly algorithm and proposed algorithm of MIMO-NOMA.

a. System Model and Problem Formulation

This paper considers multi-user MIMO system, in which the base station (BS) consists of M antennas transmit data to multiple receivers, each consist with N antennas. Now the total number of users in the system is M X L, which are grouped into M clusters randomly with L(L≥2) users per group. Non-orthogonal multiple access employes among the users in the same group.

The matrix of channel between the BS and the lth use in the mth cluster i.e user(m,l)(m∈{1,…….,M}), l∈{1,…………,L} is denoted as $H_{m\,l} \epsilon\ C^{N\,XM}$. the preceded matrix is used by BS is denoted as $P \epsilon C^{M\,X\,N}$

Whereas detection vector is $k_{m,l\ \epsilon} C^{N\,x\,1}$. Now they validate

(a) $S = I_M$, here I_M represent the M X M identity matrix.

(b) $|k_{m,l}\ |2$ =1 and $k_{m,l}^{H} H_{m,l} ot = 0$ for any t≠m where ot is the Tth column of S[12].

Now the number of antennas validate N≥M to make feasible. Because of the zero-forcing (ZF) based detection employed. Now the inter-group interference can be neglected even when exist multiple users in a group. Only scalar value $|\ k_{m,l}^{H}\ H_{m,l} S_m|^2$ required feedback of BS form user(m,l).

Now applies MIMO-NOMA approach, the BS multiplexes the intended signals for all users at the same frequency and time resource. Now the transmitted signals for the BS can be expressed as

$x = P_s$…………………(1)

$here\ infromation\ vector\ s\epsilon C^{Mx1}$ can be expressed as

$$= s = [\sqrt{Pmax\ E_{1,1}}\ s_{1,1+\ldots\ldots}+\ \sqrt{Pmax E_{1}, L\ S_{1,L}}\ \sqrt{Pmax\ E_{(m,l)}}\ s_{M,1}+\ldots\ldots\ldots+\ \sqrt{Pmax E_{M,L}}\ s_{M,L}]\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Here $s_{m,l}$ and $E_{m,l}$ represent the signal and power allocation coefficient for user(m,l) satisfying

$\sum_{m=1}^{M}\sum_{l=1}^{L}\ E_{m,l}\ \ \leq 1$ Pmax represents the total transmit power for the BS.

$henece\ the\ estimated\ signal\ is\ given\ by$

$y_{m,l=H_{m,l}P_s} + n_{m,l}\ldots\ldots\ldots\ldots\ldots\ldots(3)$

$here\ n_{m,l}\ is\ additive\ white\ gaussian\ noise\ vector, CN(0,\sigma^2 I)$

now the detection vector $k_{m,l}$ to the estimated signal(3) expressed as

$$k_{m,l}^{H}\ y_{m,l}\ = k_{m,l}^{H}H_{m,l}P_m\ \sum_{l=1}^{L}\sqrt{Pmax}\ E_{m,l}\ s_{m,l}\ + \sum_{t=1,t\neq m}^{M}K_{m,l}^{H}\ H_{m,l\ Pktk}\ \ + k_{m,l}^{H}\ n_{m,l}\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

$here\ tk\ reprents\ the\ th\ \ kth\ row\ of\ t.$

the condition define for detection vector that is $k_{m,l}^{H}H_{m,l}ot\ = 0\ for\ any\ t \neq m, (4)\ can\ be\ simplified\ as$

$$k_{m,l}^{H}y_{m,l}\ = k_{m,l}^{H}H_{m,l}P_m\ \sum_{l=1}^{L}\sqrt{Pmax E_{m,l}\ s_{m,l}}\ \ + k_{m,l}^{H}\ n_{m,l}\ldots\ldots\ldots\ldots(5)$$

$now\ effective\ channel\ gains\ are\ are\ ordered\ as$[12]

$$|\ k_{m,l}^{H}\ H_{m,l}P_m|^2 \geq\ldots\ldots\ldots\ldots\ldots\ldots \geq |\ k_{m,L}^{H}\ H_{m,L}\ P_m|^2\ldots\ldots\ldots\ldots(6)$$

Employing at receivers end each user acts SIC to remove the interference form users with worse channel gain that is the interference form user(m,l+1),…………,(m,L) is removed by user $(m,l)^2$.

Hence achieved data rate at user(m,l) is given by[13]

$$X_{m,l}\ = \log_2(1 + \frac{\rho E_{m,l}\ |\ k_{m,l}^{H}\ H_{m,l}\ p_m|^2}{1 + \rho\sum_{k=1}^{l-1}E_{m,t}\ \ |k_{m}^{H}\ H_{m,l}\ p_m\ |^2})\ldots\ldots\ldots\ldots(7)$$

$here\ \rho\ = {}^{Pmax}/_{\sigma^2}$ represent the transmit signal-to noise ratio (SNR).

Problem formulation

The total power consumption is combination of two power factor such as circuit power Pc and flexible transmit power Pt= $P_{max}\ \sum_{m=1}^{M}\sum_{l=1}^{L}E_{m,l}$ as to [16]

Now defined the EE of the system as

$$\eta EE\ = \frac{X^{sum}}{P_c + P_t}\ldots\ldots\ldots\ldots(8)$$

Here $X^{sum}\ = \sum_{m=1}^{M}\sum_{l=1}^{L}R_{m,l}$ represent the achievable sum rate.

Our objective to maximize the EE of the system when each user has a predefined minimum rate. The problem can be formulated as

$$\max_{E\ m,l}\eta EE\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

Such that $X_{m,l}\ \ \geq\ X_{m,l}^{min}, m\epsilon\{1,\ldots\ldots\ldots\ldots\ldots, M\}, l\epsilon\{1,\ldots\ldots L\}\ldots\ldots\ldots\ldots(10)$

$$\sum_{m=1}^{M}\sum_{l=1}^{L} E_{m,l} \leq 1 \ldots\ldots\ldots\ldots (11)$$

Here (10) and (11) denotes the users minimum rate requirements and transmit power constraints.

b. Deep Learning

The deep learning is advance version of artificial neural network and its consist of three layers such as input, hidden, and output. The input and output layer are single layer and hidden layers may be extended to multiple layers depending on the complexity of the processing algorithm. the development of deep learning model represents in figure (1)[20]

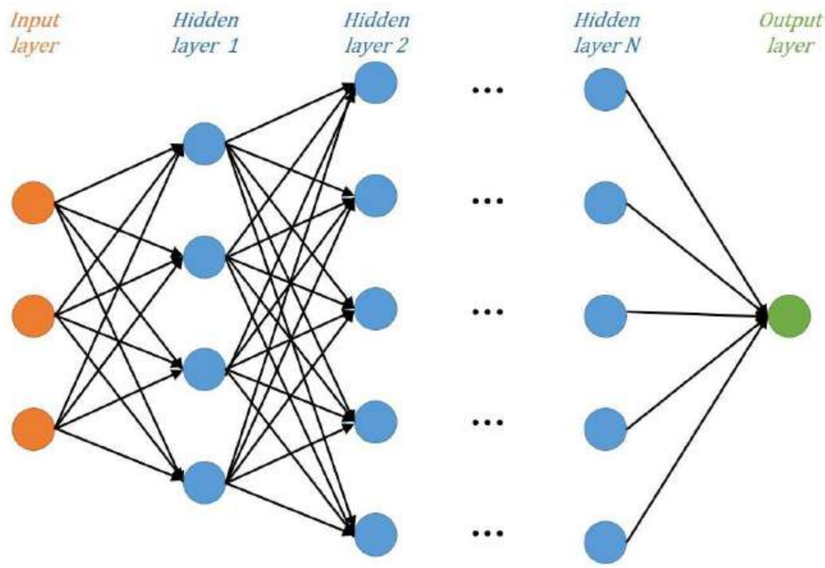

Figure 1: development of deep neural network model

There are two important factors of the relation between adjacent layers are linear and nonlinear. The linear relationship connects input layer and output layer with operators of multiplication and addition. Instead of that non-linear relation handle the process of activation function

Consider that output of the (x-1)th layer is Yn-1, the weight matrix of the xth layer is Wn, the bias vector is bn and the oupt of the n-th layer yn can be expressed as

$$y_n = f(w_n . y_{n-1} + b_n) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

The performance of deep learning algorithms depends on activation function. Deep learning consists of several activation function such as sigmod function, tanh functions, and rectified linear unit (ReLU). The majors of deep learnings have convolutional neural network (CNN), recurrent neural network (RNN), deep neural network (DNN), and long- short term memory networks.

b.1 CONVOLUTIONAL NEURAL NETWORK (CNN)

The CNN is set of input layer, convolutional layer, pooling layer, fully connected layer and output layer. The varying capacity o layers robust the CNN classifier for the classification and detection of user. consider that the input features of CNN are map of layer x is Mx(M0=F). now the convolutional process can be expressed as

$$Mx = f(C_{x-1} \otimes Wx + bi) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Here Wx is the convolutional kernel weight vector of the x layer, the symbol $\otimes$ represents convolutional approach, bi is the offset vector of x layer. F(x) is the activation function.

By providing various window values, the convolutional layer extracts various feature information from the Channel matrix Mi1 and various feature information from the data using various convolution kernels. By sharing the same weight and offset throughout the convolution operation, the same convolution kernel adheres to the notion of "parameter sharing," significantly reducing the number of parameters used by the complete neural network. Following the convolutional layer, the pooling layer typically samples the feature map using various sampling algorithms. The pooling layer may be written as follows if Cx is the input and Cx+1 is the output of the pooling layer.

$$C_{x+1} subsampling\,(Cx) \ldots\ldots\ldots\ldots\ldots\ldots .(14)$$

The window region's mean or maximum value is typically chosen by the sampling criterion. The pooling layer primarily minimizes the feature's size, which lessens the impact of redundant features on the model.

B.2 LSTM

The LSTM is a type of RNN that is connected to other nodes in the same layer to enhance learning by eradicating and retaining particular information. The LSTM model's flow graph is shown in Figure 2. It consists of a dropout layer with a rate of 0.5 after the first LSTM layer with a 128 kernel and Adam activation function. A dense layer with a sigmoid function receives input from a fully connected layer that receives output from the dropout layer and uses it to classify interference fee subchannel allocation[27].

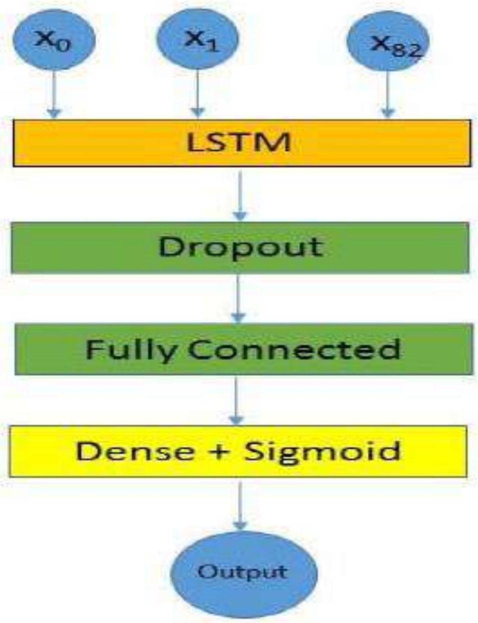

Figure 2: LSTM model for resource optimization

B.3 RNN

Recurrent neural networks (RNNs) are a subset of supervised learning algorithms. They can model sequential data for estimation and recognition. RNNs are made up of higher-dimensional hidden layers made of artificial neurons with non-linear feedback loops. As a result, RNNs have two inputs: the current sample and the recent past sample, as illustrated in Figure, where the recent input is the non-looping input to each neuron and the recent past is the output that loops back into the network[26]. The hidden layers can act as memory for the network state at a given point in time, which is dependent on its previous state. This design allows RNNs to save, recall, and process previously complex data for an extended period of time. RNNs can also map a specific input to an output sequence during the current time period and forecast this sequence during subsequent time periods. The dispersion of a transmitted signal through a fading channel produces an expanded signal with long-term dependencies between its samples. These dependencies differ from one signal to the next and do not follow a consistent pattern. Using a feed-forward (FF) neural network to model long-term dependencies will necessitate a high-dimensional feature space and a large number of neurons, which will result in over-fitting and sub-optimality. Figure 3 represent the processing of RNN network.

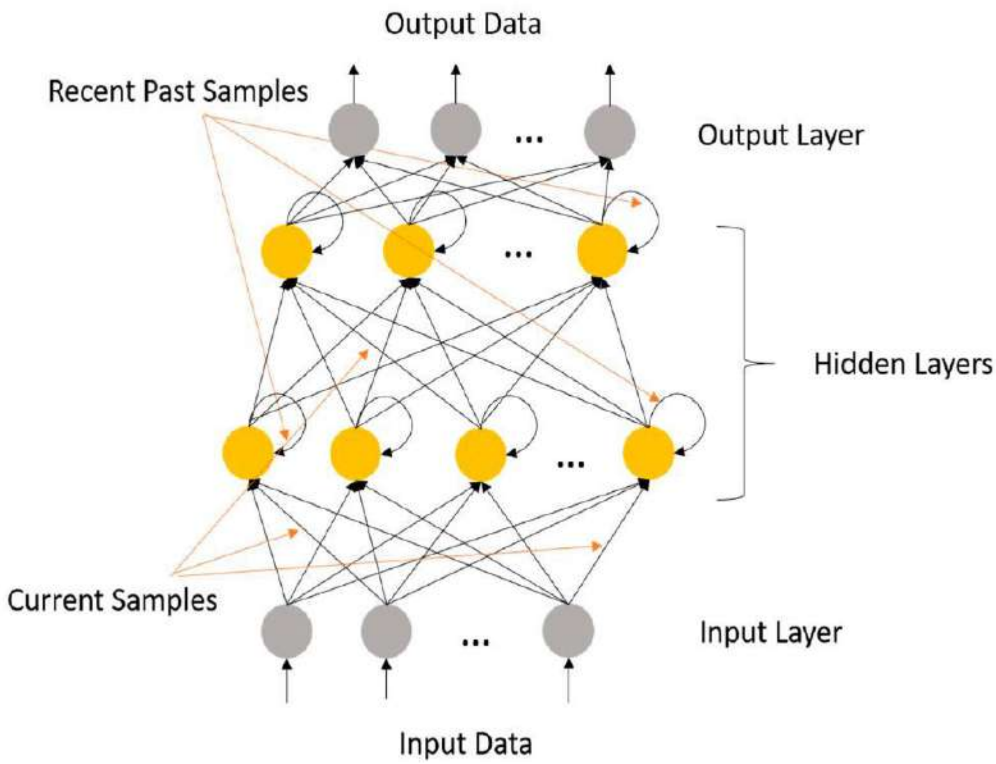

Figure 3: The processing block of RNN networks.

c. Firefly Algorithm

Firefly is nature inspired meta-heuristic function for the process of dynamic optimization of features component of data. this algorithm is proposed by Xin-She Yang by the concept of light emitting by the fireflies. The high intensity of bioluminescence collection property influences the capacity of algorithm. The major physical property of firefly is unisexual [36]. The process of algorithm describes here

1. Randomly generate the population of fireflies.
2. Define the parameters of FA algorithm
3. Estimate the fitness constraint's function define by objective function
4. Estimate the relative distance between fireflies and attractiveness
5. Update the position of firefly
6. Derive new firefly
7. Rank the fitness constraints
8. Return optimal firefly
9. Exit

d. Methodology MIMO-NOMA-CNN

The proposed model of MIMO-NOMA-CNN is resolving issue of power allocation. the processing of model mapped feature of channel vectors, transmit power, power allocation factors and AWGN. and search all power allocation approach as non-linear. The proposed model employed rectified linear active function for the training of the networks. The ReLU function describes as

$$f_{ReLU\,(x)} = max(0, x)\ldots\ldots\ldots\ldots\ldots\ldots(15)$$

Here x defines the argument of the function. Also consider O and xin to be the output of the network and the input of the MIMO-NOMA system, the expression can write as

$$O = f(x_{in}, w) = f^{(n-1)}(f^{(n-2)}(\ldots f^{1}(x_{in})))\ldots\ldots\ldots\ldots(16)$$

Where n and W are defined as the number of layers of the network and the weight of the network respectively. Figure 4 process of CNN mode for MIMO-NOMA.

Processing of CNN

1. The input of network is channel vector k_m and transmit power and precoding matrix P_m
2. After the processing of channel vector and other parameters employe firefly algorithm. the employed firefly algorithm removes local interference and improve the process of feature mapping.
3. The layer of convolutional network 64 different 4 X 4X1 filters and 1 stride produces feature map follows ReLU.
4. Employed the power allocation constraints for next layer for the selection of lower transmit power. The constraints of power is $P\sum_{m=1}^{M}|p_m| \leq P_t$
5. The layer of fully connected to process of power allocation factors. The total numbers of neurons is 256.
6. The output of FC layer is proceed in 3X3X1 filter of convolutional layers filter and stride 1
7. The maximum pooling of network filter is 3X3X1
8. The total number of convolutional layers is 11
9. Finally estimates optimal preceded matrix P_m
10. Allocate optimal energy for transmission of signal.
11. Exit

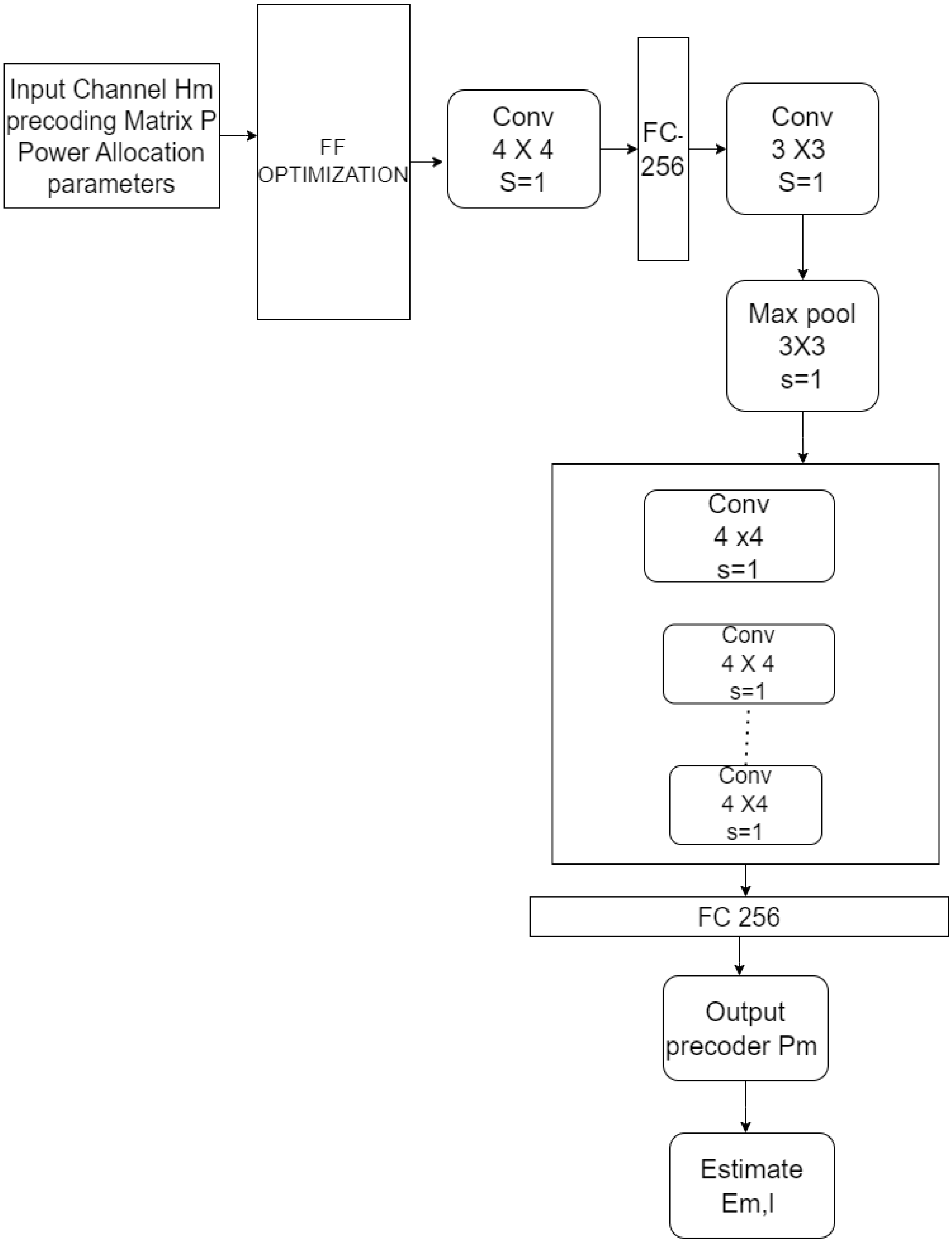

Figure 4: process of network consist of 11 layers of convolutional, max pool and fully connected 256 neurons. Also contains firefly process block for optimization of local interference removal.

Table 1: parameters value of CNN network

Algorithm	Parameter	Values
CNN	Layer	11
	Activation function	ReLU
	Optimizer	FF
	Loss	Binary cross entropy
	Epochs	200
	Validation _split	2
	Batch size	500

IV. EXPERIENTIAL ANALYSIS

In this section examine the performance of the proposed CNN approach for optimization of resource optimization in MIMO-NOMA communication system. The objective of this paper is enhancing the utilization of energy and improvs sum rates of data. to employed deep learning algorithm uses tensor flow 1.8 on windows operating system with 64GB RAM. The employed software was MATLAB version 2016R. for the validation of algorithm others algorithm is simulation such as RNN, LSTM, CNN and DNN. The simulation parameters mention in table 2

Table 2: Simulation parameters of NOMA

Parameter	Value
Base station (BS) power	46dBm
System bandwidth	5-10MHz
Number of users per cell	10-20
Bandwidth per user	5.4 MHz
Channel matrix (Hi)	Rayleigh or Rician fading
AWGN (w)	□10 to 30 dBm

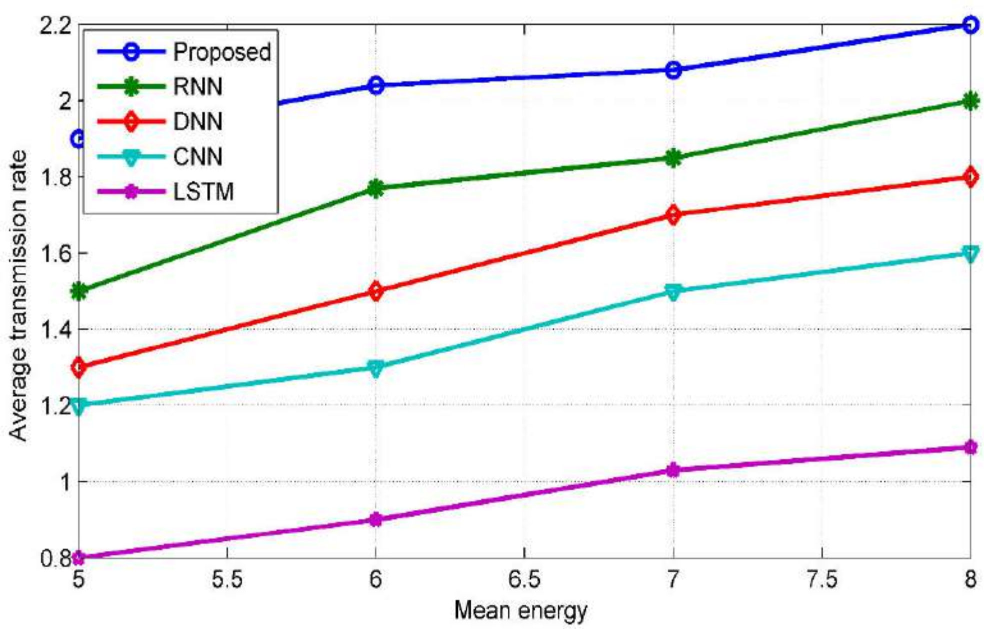

Figure: 5 compression of average transmission rate Vs mean energy for proposed algorithm and existing algorithms of deep learning.

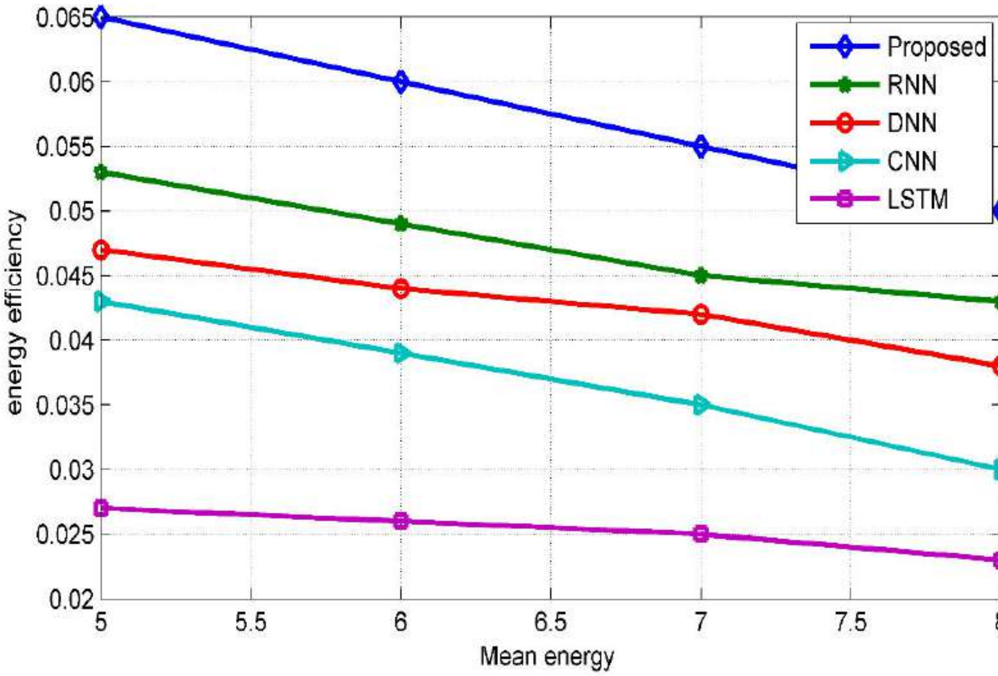

Figure: 6 compression of energy efficiency Vs mean energy for proposed algorithm and existing algorithms of deep learning.

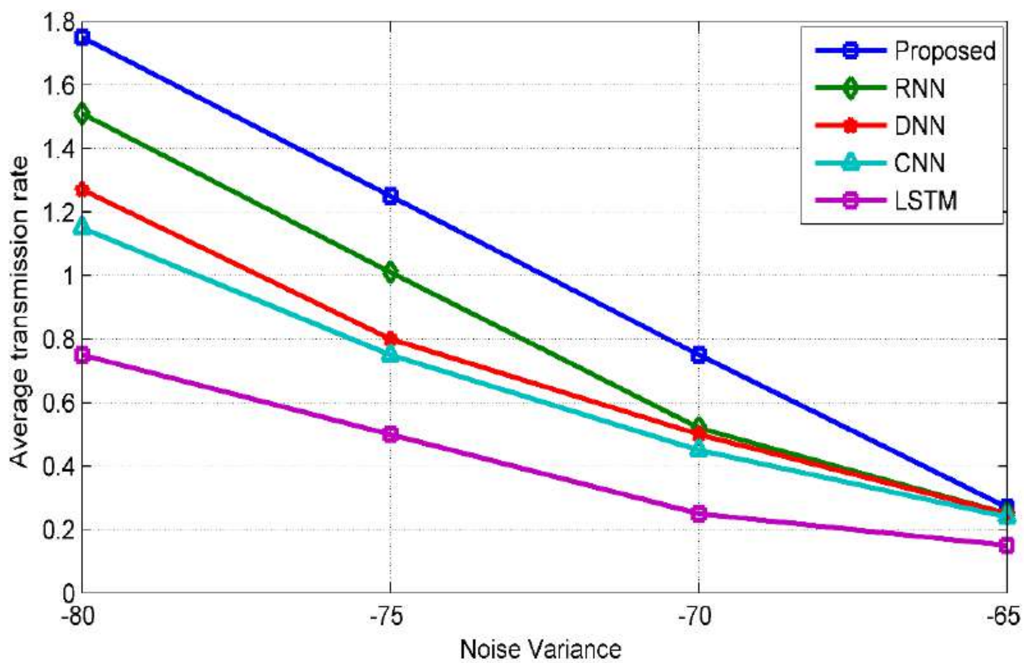

Figure: 7 compression of average transmission rate Vs noise variance for proposed algorithm and existing algorithms of deep learning.

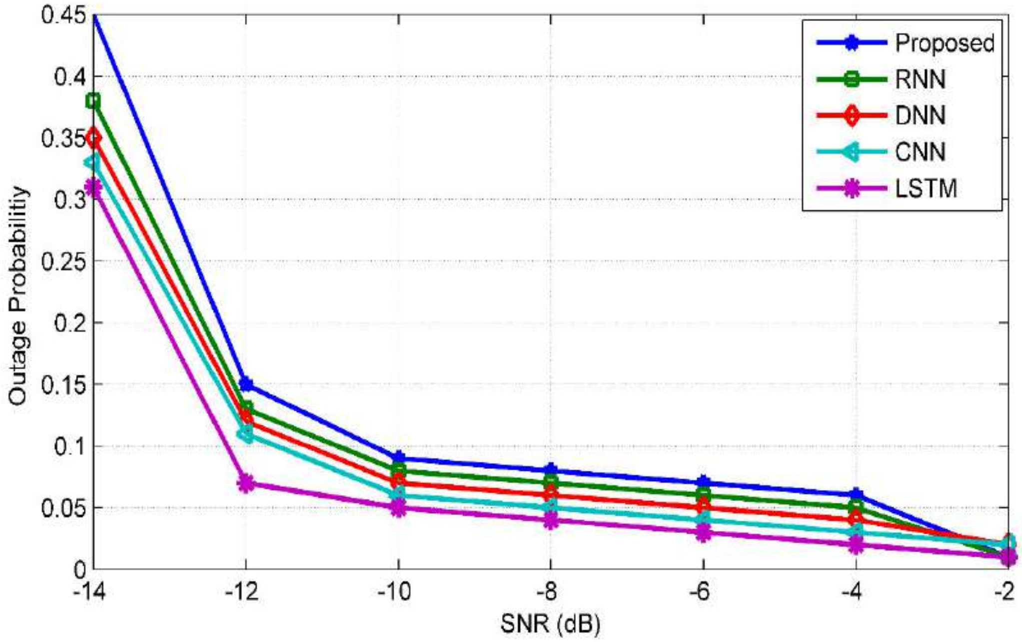

Figure: 8 compression of outage probability Vs SNR for proposed algorithm and existing algorithms of deep learning.

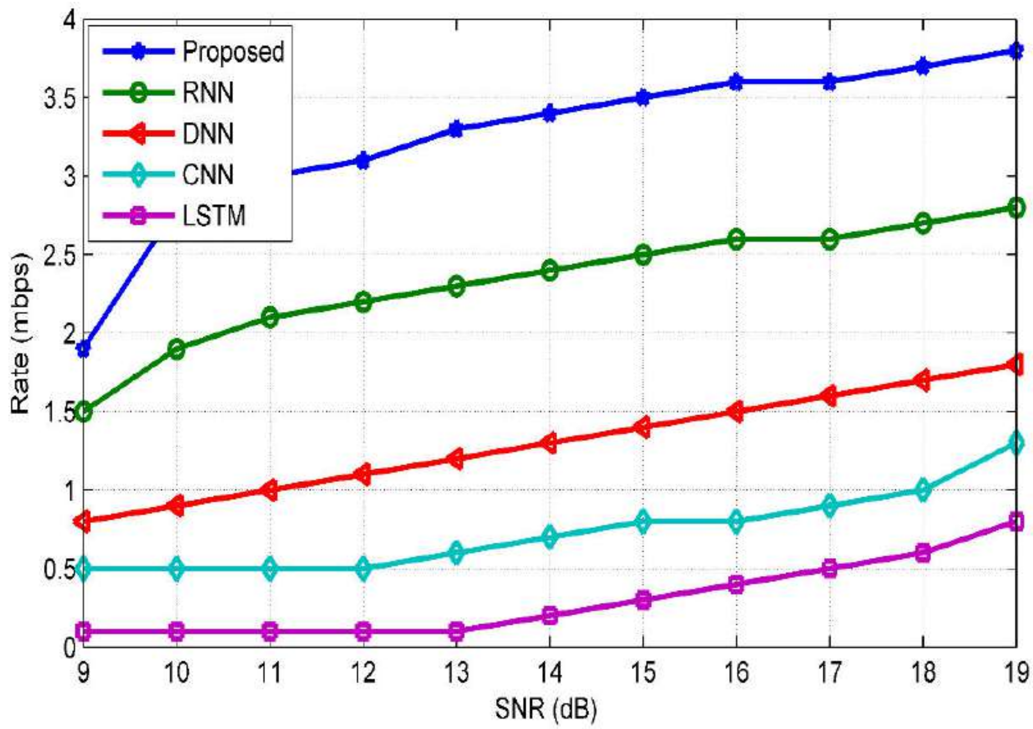

Figure: 9 compression of data rate Vs SNR for proposed algorithm and existing algorithms of deep learning.

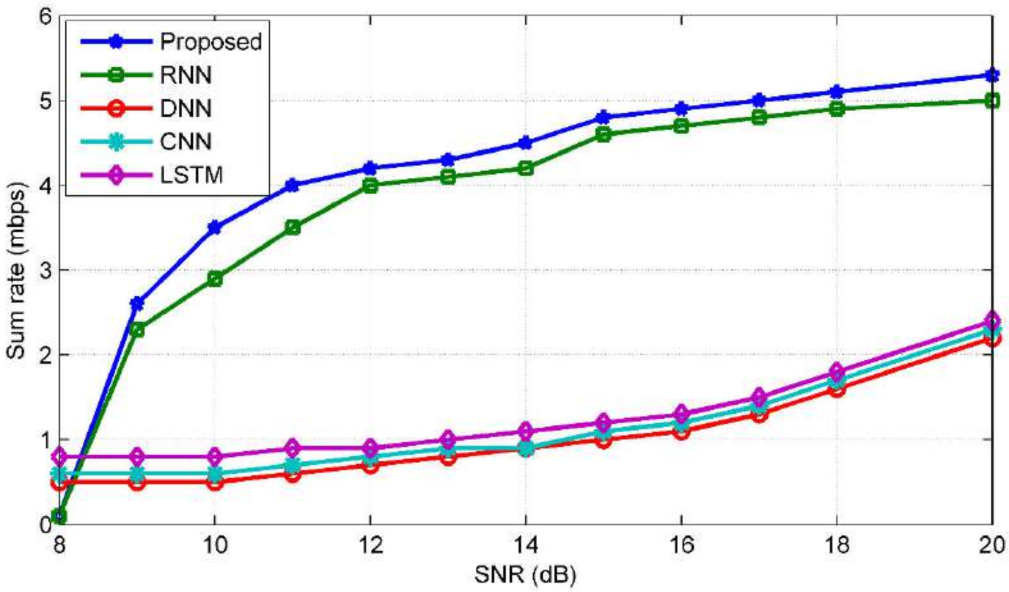

Figure: 10 compression of sum data rate Vs SNR for proposed algorithm and existing algorithms of deep learning.

V. RESULTS & DISCUSSION

This section describes the results of simulations on NOMA parameters in MIMO systems. The analysis of results consists of deep learning algorithms and parameters of MIOM-NOMA such as energy efficiency, data rate, outage probability, and sum rates of different scenarios such as signal-to-noise ratio and variance. Figure 5 depicts the average transmission rate of the MIMO-NOMA model with the employed algorithm of deep learning. The variation in mean energy impacts the average transmission rate. The proposed algorithm archives the maximum transmission rate. The achievable transmission rate indicates that the firefly algorithm employed on CNN networks removes local interference and boosts the mapping process of convolutional layers. The maximum transmission rate of the proposed algorithm is 2.2. the state-of-the-art for deep learning algorithms such as RNN, DNN, CNN, and LSTM. The RNN algorithm also outperforms CNN and has a lower transmission rate than the LSTM algorithm. Figure 6 depicts the energy efficiency of NOMA employed with the proposed algorithm with factors of mean energy. The efficiency of energy remarks that the proposed CNN algorithm very efficiently allocates power of the base station and transmission power of the user of subchannel interference. The figure shows the improved energy efficiency of the proposed algorithm compared to other deep learning algorithms. The others are deep learning algorithms such as RNN, DNN, CNN, and LSTM. The results of the DNN algorithm are also promising in terms of energy efficiency. The employed DNN algorithm does not contain any optimization algorithms, and local interference reduces the efficiency of energy. Figure 7 depicts the average transmission rate based on the impact of noise variance. The variance of noise deformed the groups of users, and the transmission rate degraded. The proposed algorithm reduces the impacts of noise variance and improves the average transmission rate. The improved transmission rate is proof that the proposed CNN algorithms reduce interference and boost the power of base stations. The RNN algorithms also reduce the impact of noise variance and boost the transmission rate. The other algorithms of deep learning suffer from noise and degrade the transmission rate. Figure 8 depicts the outage probability of the proposed algorithm based on the impact of different SNR levels. The improved outage probability enhances the performance of MIMO-NOMA. Simulated results showed that the proposed system achieved improved outage probability performance for the SNR range of 15 to 2 dB, with a maximum improvement of 10% corresponding to SNR values in the range of 14 to 4 dB. The outage probability for the proposed NOMA system was compared to that of deep learning algorithms such as RNN, CNN, DNN, and

LSTM. The lower value of the outage probability indicates the controlling interference in the NOMA system. Figure 9 depicts the quality of the data rate of the proposed algorithm in MIMO-NOMA. The improved data rate increases the value of other deep learning algorithms by 33%. The maximum data rate archives in the range of 14 to 19 SNR values. Figure 10 demonstrates that when the proposed scheme was used, the sum rate of the system increased by an average of 37% at SNR values ranging from 10 to 19 dB. Because the proposed CNN provides a more accurate indication of user channel condition, the system's total and user rates have improved. As a result, each user can adjust their data rate in accordance with the SNR conditions, achieving the highest transmission quality and, consequently, the highest rate.

Table: 3 Comparative result analysis of average transmission rate

Algorithms	Average Transmission Rate	Improvements
Proposed	1.9	0.4
RNN [16]	1.5	0.2
DNN [26]	1.3	0.1
CNN [37]	1.2	0.4
LSTM [24]	0.8	1.1

Table: 4 Comparative result analysis of energy efficiency

Algorithms	Energy Efficiency	Improvements
Proposed	0.065	0.011
RNN [16]	0.054	0.008
DNN [26]	0.046	0.002
CNN [37]	0.044	0.018
LSTM [24]	0.026	0.039

Table: 5 Comparative result analysis of average transmission rate Vs noise variance

Algorithms	Average Transmission rate	Improvements
Proposed	1.8	0.3
RNN [16]	1.5	0.2
DNN [26]	1.3	0.21
CNN [37]	1.09	0.29
LSTM [24]	0.8	1

Table: 6 Comparative result analysis of outage probability

Algorithms	Outage Probability	Improvements
Proposed	3.8	1
RNN [16]	2.8	1
DNN [26]	1.8	0.5
CNN [37]	1.3	0.5
LSTM [24]	0.8	3

Table: 7 Comparative result analysis of sum rates of data.

Algorithms	Sum rates	Improvement
Proposed	5.3	0.3
RNN [16]	5	2.8
DNN [26]	2.2	0.1
CNN [37]	2.3	0.1
LSTM [24]	2.4	2.9

Table 2 to table 7 represents the compression results of deep learning-based power allocation and interference minimization approach. the analysis of results suggest that proposed algorithm is better than maximum parameters of MIMO-NOMA systems.

VI. CONCLUSION & FUTURE SCOPE

This paper proposed firefly algorithm and convolutional neural network-based algorithm for MIMO-NOMA systems. the proposed algorithm optimized power allocation and removal of interference in groups of users. The proposed power allocation approach has been put forth to resolve the energy efficiency maximization problem under consideration. The system sum rate and computing performance are improved by the proposed power allocation and interference removal algorithm. The BS handled power distribution first. The proposed algorithm for power allocation was trained to closely resemble the FF algorithm in order to ensure higher computational efficiency. To increase the system's overall sum rate, user scheduling was carried out based on the issued power. The simulation results show that the proposed method outperforms the deep learning algorithm in terms of spectral efficiency and addresses the problem of local interference of user groups of the downlink NOMA system. Additionally, while reducing system complexity in downlink NOMA systems, the proposed method outperforms existing algorithms in the literature as well as DNN-based methods. One potential direction for the future is to expand the proposed method to optimize other performance metrics for NOMA-based systems. Another future direction that can further enhance network performance is examining the performance of the suggested optimization method in multiple antenna combination (massive MIMO) scenarios.

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