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An Effective Simulation Based Implementation Of Energy-Efficient Optimal Resource Allocation In The Noma Networks Using Deep Learning Algorithms

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Abstract
Reliability and quality of services offered by communication technology are the demands of future communication systems. The reliability of communication systems requires low latency, high data rates, and massive connectivity. The multiple input, multiple output, non-orthogonal multiple access technique satisfies the demands of future communication systems like 5G. The sudden introduction of MIMO-NOMA requirements change several factors like channel condition and complex spectral structure reduce the system efficiency and hinder its application. To overcome the limitation of channel condition and resource allocation in NOMA, the deep learning algorithm is used. The proposed algorithm enhances the energy efficiency and data rates of the MIMO-NOMA model. The proposed algorithm utilizes the convolutional neural network and firefly algorithm. The firefly algorithm used in the proposed algorithm eliminates the local interference and enhances the feature map of the convolutional layer. To verify the proposed algorithm, simulation is done in the MATLAB environment with parameters of MIOM-NOMA. The result of the simulation is compared with other existing deep learning algorithms like recurrent neural networks, long-short term memory, and convolutional neural networks. The comparative result of the analysis indicates that the proposed algorithm is efficient in power allocation and sum data rates.
Keywords: *MIMO-NOMA, Deep Learning, Quality of Service (QoS), Channel State Information (CSI), Recurrent Neural Network (RNN)*

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I. Introduction

In contemporary times, the escalating energy consumption associated with wireless communications poses a significant social and economic challenge, particularly amidst the surge in data traffic volumes. Despite this pressing issue, there has been a notable dearth of attention devoted to addressing energy-efficient resource allocation problems within Non- Orthogonal Multiple Access (NOMA)-enabled systems. In [19], authors embarked on maximizing energy efficiency while guaranteeing the minimal necessary data rate for every user, presenting a no convex fractional programming challenge. Additionally, [10, 11] proposed a gradient-based binary search power allocation method for downlink NOMA systems, albeit with high complexity, aiming to maximize energy efficiency under users' quality of service requisites. Furthermore, NOMA finds application in future Machine-to- Machine (M2M) communications as depicted in [12], where it was revealed that system outage probability can be enhanced compared to Orthogonal Multiple Access (OMA).Moreover, a comprehensive study in [13] delves into the system performance of millimeter- wave (mm Wave) networks, concurrently investigating beam forming, user scheduling, and power allocation strategies. In essence, while the proliferation of wireless communications exacerbates energy consumption concerns, NOMA offers a promising avenue for addressing this challenge. Nevertheless, concerted efforts are required to develop sophisticated resource allocation techniques that balance energy efficiency with user quality of service requirements across various NOMA-enabled communication scenarios we exploit the deep neural network (DNN), a learning-based tool to approximate the com-plicated and nonlinear function. Over the years, DNN has been effectively used in numerous applications such as image classification, machine translation, automatic speech recognition, and Go game. Recently, also applied to various wireless systems such as multiple-input and multiple-output (MIMO) detection, wireless scheduling, direction-of-arrival (DoA) estimation, and multi-user detection. In these works, DNN is used to learn a desired nonlinear function through the training process. for instance, the DNN structure to learn the mapping between the interference pattern and the optimized scheduling has been proposed. In [18], a DNN architecture for the symbol generation, encoding, and decoding in grant-free NOMA systems has been proposed. In [19], LSTM, or long short-term memory network performing the channel estimation and data detection in grant-based NOMA systems has been presented. In our framework, DNN learns the complicated mapping between the received NOMA signal and the indices of active users in the transmit signal. To be specific, the proposed scheme, henceforth referred to as deep, learns the sparse structure of device activity using a deliberately designed training dataset. It is now well-known from the universal approximation theorem that DNN processed by the deeply stacked hidden layers can well approximate the desired function [20]. In our context, this means that the trained DNN with multiple hidden layers can handle the whole proposed process, resulting in an accurate detection of the active users

II. Proposed Objectives To Be The Studied

Integration of MIMO-NOMA systems is a noteworthy development in next-generation wireless communication, offering enhanced traffic efficiency. To further augment of these systems, deep learning algorithms are employed, with a set of objectives aimed at optimizing system capacity. MIMO-NOMA, or Multiple-Input Multiple-Output Non-Orthogonal Multiple Access, systems leverage both the transmitter and the receiver have many antennas to transmit multiple data streams simultaneously, enhancing the overall traffic capacity of wireless networks. However MIMO-NOMA systems, the utilization of deep learning algorithms becomes imperative. Deep learning algorithms, a subset of machine learning techniques inspired by the structure and function of the human brain, offer unparalleled capabilities in pattern recognition, optimization, and decision-making. By harnessing the power of deep learning, the following objectives are established to MIMO-NOMA systems:

1. We examine a model of a hybrid NOMA/OMA uplink cognitive radio network that integrates energy harvesting capabilities at the Cognitive Users (CUs). In this setup, CUs powered by solar energy opportunistically utilize the licensed channel of the primary network to transmit data to a cognitive base station, employing NOMA/OMA techniques. Additionally, we implement a user-pairing algorithm to assign orthogonal frequency bands to each NOMA group post-pairing. Our approach considers power and bandwidth allocation, ensuring optimal utilization of transmission power and bandwidth by each CU while adhering to energy constraints and accounting for environmental uncertainty. The system operates on a time-slotted basis.
2. We frame the problem of maximizing long-term data transmission rate within the framework of a Markov decision process (MDP). To derive the optimal policy, we employ a deep actor-critic reinforcement learning (DACRL) framework using a trial- and-error learning algorithm. Specifically, we utilize Deep Neural Networks (DNNs) to approximate the policy function for the actor and the value function for the critic components. Through this approach, the cognitive base station can dynamically allocate transmission power and bandwidth to the CUs by directly interacting with the environment. The proposed algorithm seeks to optimise the system reward over the long term by efficiently utilizing available resources.
3. A novel approach to merging the Firefly algorithm with CNN for MIMO-NOMA systems
4. The proposed algorithm performs better electricity distribution and resource optimization.
5. The results $of\ the\ proposed\ algorithm\ is$ compared with those of existing deep learning algorithms such as LSTM, RNN, and CNN.

Minimization of group interference and improves $the\ power\ allocation\ at\ the$ base station

III. Back Ground Of Communication Systems

Grant-Free Noma

By directly transmitting messages without requesting any permissions, grant-free (GF) transmission offers promise for low latency communication. However, when a small amount of spectrum is being used by many GF users, collision scenarios may frequently occur. Through the use of multiplexing, the non-orthogonal multiple access (NOMA) technique can be a potential way to achieve high connectivity and fewer collisions for GF transmission. We employ a semi-grant-free (semi-GF) NOMA method that enables grant-based (GB) and GF spectrum resources connection and spectral efficiency. Uplink NOMA networks are studied by applying stochastic geometry methods with semi-GF protocols. For clarification, GF users are permitted to use more memory than standard GB random access systems. Whenever they have data to send, without the base station's knowledge or consent.

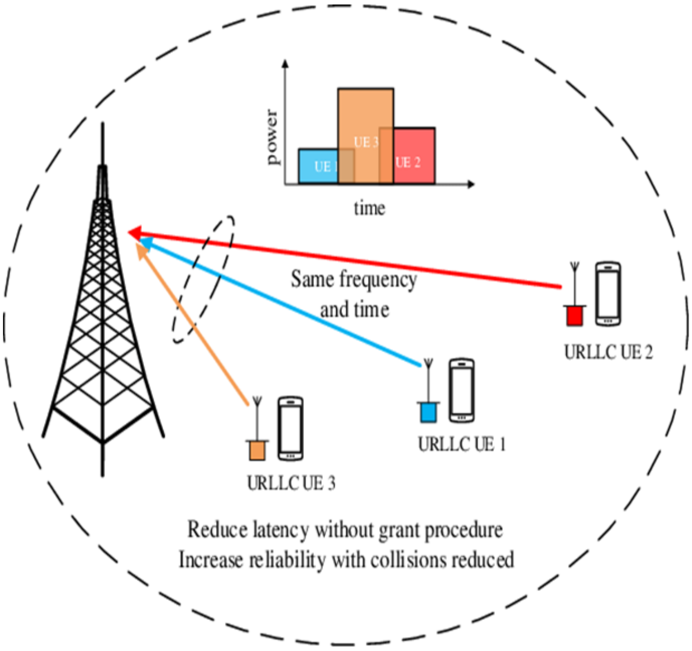


Figure 1 Block Diagram of Grant-free NOMA

Non-Orthogonal Multiple Access

This article examines non-orthogonal multiple access (NOMA), a possible solution that can assist with some of these 5G challenges. Compared to conventional orthogonal multiple access methods, NOMA can accommodate a significantly higher number of users due to its non-orthogonal resource allocation. Power-domain NOMA, multiple access with low-density spreading, sparse code multiple access, multi-user shared access, pattern division multiple access, and other similar schemes are included in our division of existing Power-domain multiplexing and code-domain multiplexing are the two primary types of NOMA techniques.

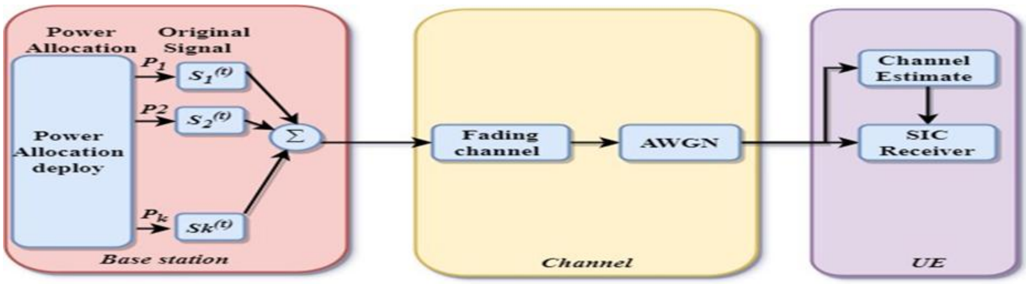


Figure 2 Block Diagram of Non-Orthogonal Multiple Access

IV. Deep Learning Algorithms

The deep learning is advance version of artificial neural network and it's 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]

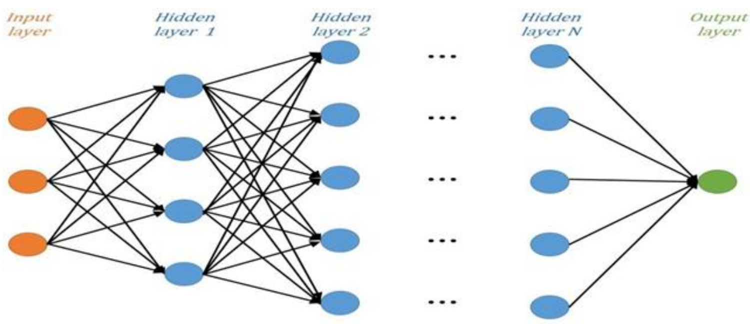


Figure 3 development of deep neural network model

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

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

The effectiveness 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 Deep neural networks, recurrent neural networks, and convolutional neural networks (DNN), and long- short term memory networks.

Convolutional Neural Network (CNN)

The input, convolutional, pooling, fully connected, and output layers make up the CNN. 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

$Mx = f(C_{x-1} \otimes Wx + bi)$ ....(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 Using a variety of sampling techniques, the pooling layer and convolutional layer normally sample the feature map. If Cx is the input and Cx+1 is the output of t, then the pooling layer can be expressed as follows. The pooling layer.

$C_{x+1} subsampling(Cx)$ … … … … … … . (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.

STM

The LSTM is a kind of RNN where specific information is removed and retained to improve learning through connections to other nodes in the same layer. Figure 2 displays the flow graph for the LSTM model. Following the initial LSTM layer with a 128 kernel and Adam activation function is a dropout layer with a rate of 0.5. A fully connected layer receives output from the dropout layer, and a dense layer with a sigmoid function receives input from this layer and uses it to classify interference fee sub channel allocation [27].

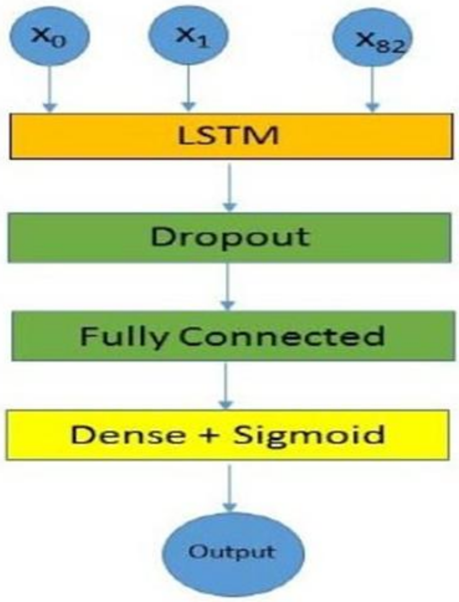


Figure 4 LSTM model for resource optimization

RNN

Supervised learning methods comprise a subset known as recurrent neural networks (RNNs). Sequential data can be modelled by them for recognition and estimation. Higher-dimensional hidden layers composed of artificial neurons with non-linear feedback loops comprise RNNs. Consequently, RNNs have two inputs: the recent past sample and the current sample, as shown in Figure, where the recent past is the output that loops back into the network and the recent input is the non-looping input to each neuron [26]. Depending on its prior state, the hidden layers can serve as memory for the network's state at any given time. RNNs can store, retrieve, and process more complicated data over time thanks to its design. Additionally, RNNs have the ability to foresee an output sequence in the future and map a particular input to it in the present. A transmitted signal that has been dispersed over a fading channel expands and develops long-term dependency between its samples. These relationships exhibit variability between signals and lack a regular pattern. A high-dimensional feature space and a large number of neurons are required for modelling long-term relationships with a feed- forward (FF) neural network; this will lead to over-fitting and sub-optimality. The RNN network's processing is shown in Figure 3.

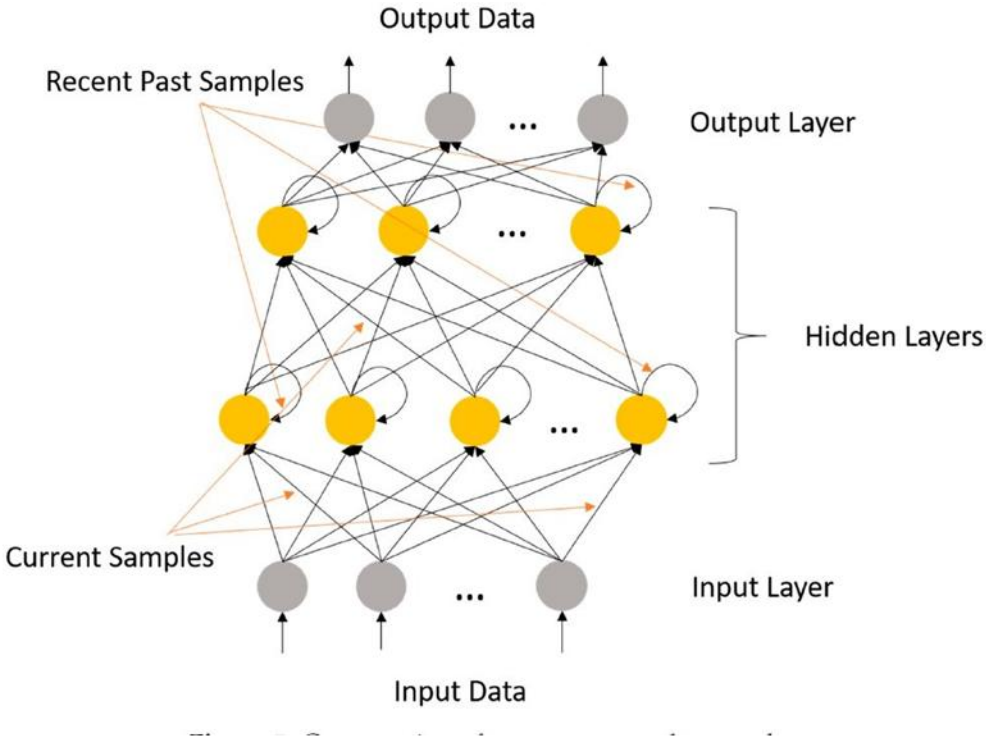


Figure 5: The processing block of RNN networks.

V. Proposed Algorithm

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

$f_{ReLU(x)} = max(0, x)$ .... (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

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

Where n and W are defined with the weight of the network and its number of layers 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 $P\sum^{M}|p_m| \leq P_t m$=1
5. The layer of completely integrated into the electricity distribution process 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

VI. Simulation Result Analysis

Table 1. Parameters for the simulation.

Parameter	Description	Value
M	Number of groups	3
Ttot	Time slot duration	200 ms
τss	Sensing duration	2 ms
W	Total system bandwidth	1 Hz
Ebat	Battery capacity	30 μJ
ess	Sensing cost	1 μJ
e tr	Transmission energy	0, 10, 20 μJ
ξavg	Mean value of harvested energy	5 μJ
μ	Initial belief that the primary channel is free	0.5
PFF	Transition probability of the primary channel from state F to itself	0.8
PBF	Transition probability of the primary channel from state B to state F	0.2
Pd	Probability of detection	0.9
Pf	Probability of false alarm	0.1
σ 2	Noise variance	-80 dB
γ	Discount factor	0.9
αa	Learning rate of the actor	0.001
αc	Learning rate of the critic	0.005
e	Epsilon rate	1 → 0.01
ed	Epsilon decay	0.9999
L	Number of episodes	300
T	Number of iterations per episode	2000

Table .2 Comparative performance of Proposed, LSTM, LSTM-E, and BI-LSTM, using parameters average transmission rate (bps) and Training episodes.

Average transmission rate (bps)				
Training episodes	**Proposed**	**LSTM**	**LSTM-E**	**BI-LSTM**
1	1.02	1.03	1.02	1.03
50	1.7	1.7	1.6	1.6
100	1.8	1.7	1.6	1.5
150	1.8	1.7	1.6	1.5
200	1.8	1.7	1.6	1.5
250	1.8	1.7	1.6	1.5
300	1.8	1.7	1.6	1.5
350	1.8	1.7	1.6	1.5
400	1.8	1.7	1.6	1.5

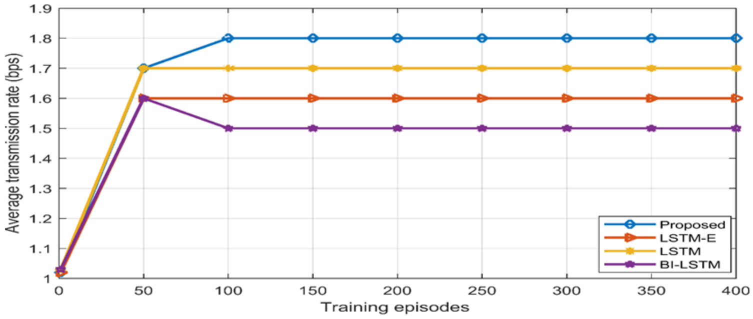


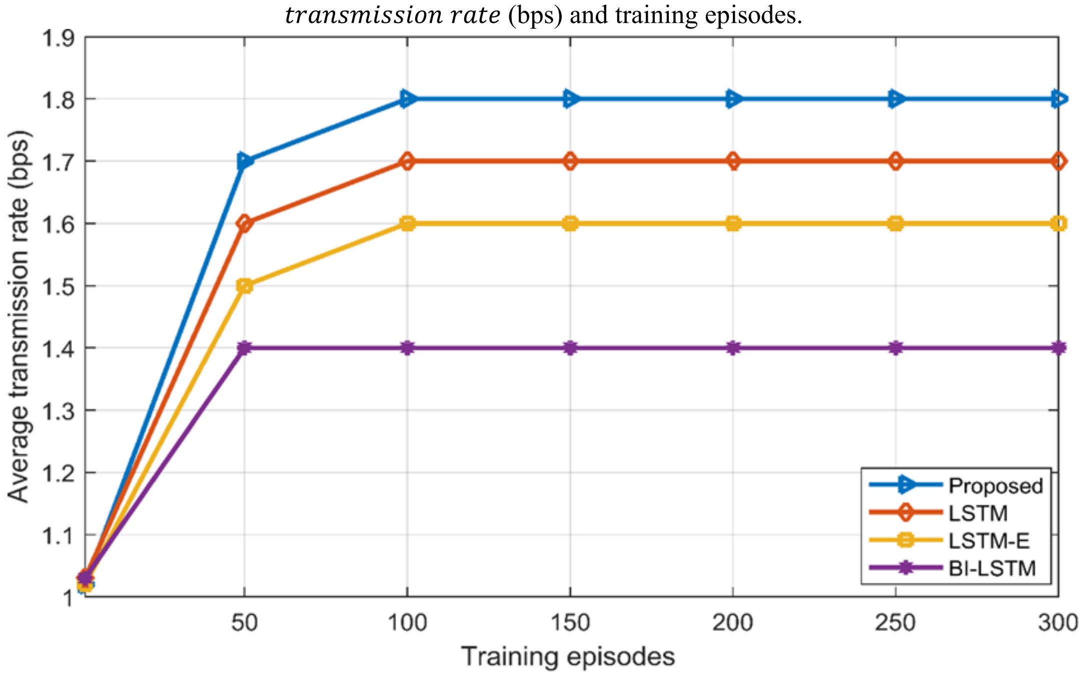
Figure: 6 Comparative analysis of using proposed, LSTM-E, BI-LSTM, and LSTM, techniques with *average transmission rate* (bps) and training episodes.

We observe that the proposed method is better than the remaining three methods, which are LSTM, LSTM-E, and BI-LSTM. Thus, the value of proposed training episodes 100 is 1.8, which is better than other methods. The value of LSTM is 1.7, *the value of* LSTM-E is also less, which is 1.8, *and the value of* BI-LSTM is also 1.5. Which is less than other methods.

Table 3 Comparative performance of Proposed, LSTM, LSTM-E, and BI-LSTM, using parameters average transmission rate (bps) and Training episodes.

Average transmission rate (bps)				
Training episodes	**Proposed**	**LSTM**	**LSTM-E**	**BI-LSTM**
1	1.02	1.03	1.02	1.03
50	1.7	1.6	1.5	1.4
100	1.8	1.7	1.6	1.4
150	1.8	1.7	1.6	1.4
200	1.8	1.7	1.6	1.4
250	1.8	1.7	1.6	1.4
300	1.8	1.7	1.6	1.4

Figure: 7 Comparative analysis of using proposed, LSTM-E, BI-LSTM, and LSTM, techniques with *average transmission rate* (bps) and training episodes.



We *observe that the proposed* method is better than the remaining three methods, which are LSTM, LSTM-E, and BI-LSTM. Thus, the value of proposed training episodes 100 is 1.8 which is better than other methods. The value of LSTM is 1.7, the value of LSTM-E is also less, which is 1.6, and the value of BI-LSTM is also 1.4. Which is less than other methods.

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