ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20221228104420
Original scientific paper

Deep Learning Technique for Power Domain Non-Orthogonal Multiple Access Using Optimised LSTM in Cooperative Networks

Kavitha GOPALUN*, Deny John SAMUVEL

Abstract: Non-orthogonal Multiple Access (NOMA) is the technique proposed for multiple accesses in the fifth-generation (5G) cellular network. In NOMA, different users are allocated different power levels and are served using the same time/frequency Resource Blocks (RBs). The main challenges in existing NOMA systems are the limited channel feedback and the difficulty of merging them with advanced adaptive coding and modulation schemes. The 5G system in NOMA aims to access low latency, efficiency in superior spectra, and balanced user fairness. NOMA allows multiple users with different power levels to share resources in radio frequency time. The existing Orthogonal Multiple Access (OMA) system produces high latency, high computational complexity, and throughput complexity in modifying wireless channels. To overcome these issues, this paper proposed optimising deep learning-based power domain NOMA of Long Short-Term Memory (LSTM) with particles Swarm optimisation (PSO) technique. This proposed work (LSTM-PSO) is deployed with a Cooperative network model. The advantage of LSTM-PSO in Cooperative Non-orthogonal Multiple Access (CNOMA) is that it provides high performance, better utilisation of downlink, efficiency in sharing of resources, enhancing the activity of users, capacity of the base station and improving quality of service, estimation of channel condition. LSTM-PSO got a higher accuracy rate of 92.05%, LSTM got 86.45%, PSO got 88.13%, and the accuracy rate of ANN and DNN was 83.76% and 84.70%.

Keywords: cooperative networks, LSTM, NOMA, optimization, PSO, 5G system

1 INTRODUCTION

Non-orthogonal Multiple Access (NOMA) is one of the radio access techniques for performing cellular communication in next-generation technology. That is, analogue-based phone calls via IP services like voice calls, video calls, message transformation etc., are required to meet the new generation's technology. NOMA is used in 5G technology for realising aggregate goals like balanced user fairness, low latency, and spectral efficiency [1]. With the increasing requirement of a wireless network for accessing a large capacity of complex data, this 5G technology explodes the huge volume of accessing data using various techniques. To improve the spectrum efficiency in large-scale-based Multiple-Input Multiple Output (MIMO), ultra-massive wireless connectivity and communication based on millimetre-wave are the main goals of next-generation wireless networks [2]. The wireless communication network can control many passive reflective elements like spectrum and energy efficiency. Implementing these efficiencies in the wireless network requires intelligent reflecting surfaces (IRS). Implementing a hybrid wireless network, the IRS enhances the significant performance with active wireless network components comprising traditional network activities [3].

The physical layer security of wireless network jointly implements the passive beam forming and active beam forming algorithm by calling the IRS-based NOMA technology in the wireless networks and also enhancing the spectrum efficiency by comparing it with traditional OMA techniques like TimeDivisionMultiple Access (TDMA) [4]. To improve the principles of NOMA in reliability and efficiency, the basic things needed are Bit Error Ratio (BER) and allocation of resources is carried out [5-7]. The downlink scheme of NOMA-based technology uses a random selection of users to transmit signals in a unicast-multicast system, which many multicast users can access. In addition, the fairness approach of the NOMA technique deployed that pairing of the cell-edge users, which are closer to the base station (BS) and will automatically improve the ergodic capacity [8, 9].

The traditional method of OMA eliminates the interfering signals and assigns the orthogonal resources to the active users. The principles are based on Frequency Division Multiple Access (FDMA), Time Division Multiple Access (TDMA) and Code Division Multiple Access (CDMA). At the same time, the NOMA technique is considered for implementing the technique for accessing the resources by multiple users within a single resource block concerning time, spreading code, and frequency channel. The basic ideas of sharing the resources are categorised into two types, namely code-domain NOMA and PD-NOMA. It includes Sparse Code Multiple Access (SCMA) and Low-Density Spreading (LDS). It supports multiple users for implementing the power domain multiplexing. That means it allows multiple users to use the PD-NOMA because it provides better network connectivity and its bandwidth is shared by users. PD-NOMA is more compatible with existing wireless networks [10].

2 RELATED WORKS

The third generation of mobile systems is based on the scheme of Wideband CodeDivision Multiple Access (WCDMA). Through this scheme, it transmits the movies at a moderate data communication speed. The improved version of the 3G pack is High-Speed Packet Access (HSPA) and HSPA+ (3.5G). When comparing it with the Wi-Fi and wireless LANs, streaming of moving images is slower even though it has data rate in higher. To raise the speed of communication more than six times better when compared with 3G technology, the Long-Term Evolution (LTE) of 4G is used. The advanced version of the 4G network is closer to the Wi-Fi network; it uses LTE based 4.5G network.

Wireless data communication is increasing daily, and it requires a new scheme for speeding up the process of accessing data. Therefore, improving the storage capacity of data and transmission rate of data is essential. So 5G technology is implemented [11]. Mu et al. [12] proposed IRS based NOMA system for utilising the sequential rank to identify the sequential-based rank-one constraint with optimal rank-one solution in the local network communication system. Fu et al. [13] implemented the optimisation of transmitting data signals by using beam formers in the BS and IRS-based phase shift matrix of the NOMA network. Implementing this concept, it requires the Reinforcement Learning (RL) technique. A novel IRS-based wireless communication network framework in a NOMA-based model uses a passive beamforming design [14]. Tab. 1 shows the survey on NOMA techniques.

The paper has been organised as follows: Section 2 discusses a Review of Literature, Section 3 describes the implementation of NOMA-based technique using LSTM-PSO in a cooperative network, Section 4 includes results and analysis, and Section 5 describes the conclusion and future work.

3 PROPOSED LSTM COOPERATIVE NETWORK METHODOLOGY

In this section, we discussed data transmission in an efficient way, with low latency, and less power consumption. The 5G technology requires a non-orthogonal multiple access system with LSTM-PSO in a cooperative network. The architecture of the proposed work is given in Fig. 1. Multi-users in the cluster form with the cooperative network are equipped to enhance the utilisation of downlink and power domain to improve performance by applying a direct transmit link between the base station and its users in the cooperative network. While sharing the resources, the transmission power of various users is different because of near-far issues. Therefore, it needs to detect the user's signals by employing the successive interference cancellation (SIC) operation. NOMA can detect the power domain in terms of time and frequency of users. Two types of NOMA concepts are available. They are cooperative NOMA and non-cooperative NOMA.

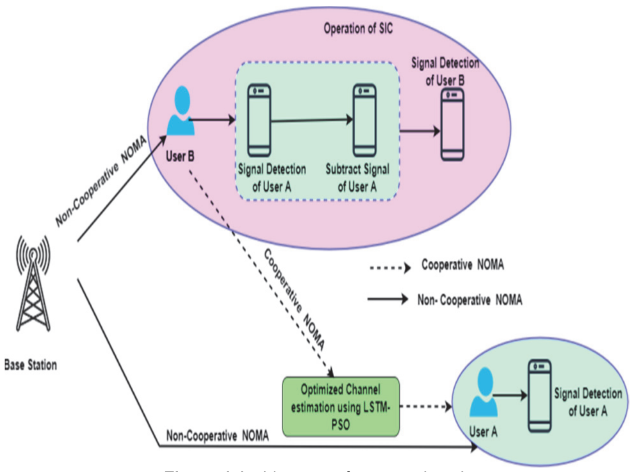

Figure 1 Architecture of proposed work

In the non-cooperative NOMA, the operation of SIC detects the signal of the reference user, regenerates the signal and discards the user's signal when its power is of higher value than the reference user. Therefore, if the base station is closer to the user, a signal is not cancelled because of its power control, and it represents the interference that degrades its performance. Similarly, the cooperative NOMA structure cancels signals interfering with the users 'and considers the users who are closer to the base station. In cooperative NOMA, the users closer to the base station are detected and subtracted from the far user (powerful) to the base station and send the air copies to far-powerful users. From Fig. 1, User B is closer to the Base Station (BS) and is considered a strong user because of using SIC operation. It has stronger channel complexity. Then it first detects the more powerful User A and subtracts the signal from the received signal before detecting User B's signal. Let us consider cooperative NOMA User B transmits the detected signal of User A through the air. In non-cooperative NOMA, a signal of User A is corrupted by the less power signal of User B, and the operation of SIC does not detect it.

3.1 System Model

The proposed system architecture contains a single base station with n users. All n users are deployed at various distances from the base station in the same frequency bandwidth. In the NOMA, all users are represented as $user_1$, $user_2$, …, $user_n$. The signal is transmitted from the base station to closer users and too far users. The channel condition of the closer user is a more superior power domain than that of the far user. As per the principle of NOMA, the better channel condition needs lower transmitted power domain. The signal transmitted by base station is represented by:

$$Q(t)=\sum_{N=1}^{N}Q_n(t)\sqrt{\gamma_n pow_t} \tag{1}$$

Here, pow_t - transition of power by the base station, γ_n - allocation of power factor in all users $user_n$ which is denoted as:

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

The transition signal may contain Gaussian noise. Therefore, the received signal of $user_i$ can is stated as:

$$P_i=hc_i q_i+\sum_{j\neq i}^{n}hc_j q_j+gn_i \tag{3}$$

Here, hc_i is the coefficient of the unknown channel from the base station to $user_i$. q_i is the transmitted signal at $user_i$. The base station transmits the signal with noise to n users and then $\sum_{j\neq i}^{n}hc_j q_j$ by subtracting the noise gn_i in the signal. The algebraic transformation of Eq. (3) is shown as:

$$P_i=ych^T+gn_i \tag{4}$$

Here, y and ch^T are vector value of signal and channel. The signal vector space can be represented as ch = [ch_1, ch_2, ..., ch_n] and y = [y_1, y_2, ..., y_n].

3.2 Channel Estimation Using LSTM Induced with PSO in the Cooperative Network

The wireless communication network in NOMA uses LSTM induced with PSO in a cooperative network. Fig. 2 shows the architecture of LSTM in the Cooperative Network.

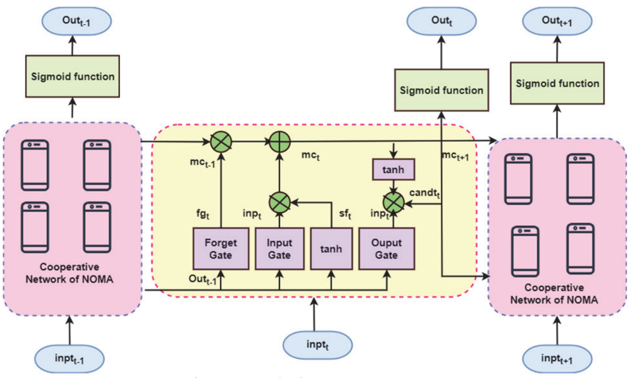

Figure 2 Structure of LSTM in cooperative network

LSTM model is used to transmit the signal in a vector-based data sequence, and it has memory cells for storing and accessing data signals and transmitting the data signal in the cooperative network of NOMA, which detects the channel capacity with the help of LSTM. The LSTM efficiently utilizes past input time series with the long-term transmission of data signal based on the time series.

In Fig. 2, LSTM contains an input layer, a hidden layer, and an output layer. The hidden layer of LSTM includes various gate units like forget gate, input gate and output gate. These gates are used for controlling the transit of data from one user to another user. The channel estimation model of LSTM uses t time instance for transmitting the signal. $inpt_t$ is the input; out_t is the output of i^{th} user at an instance time t. mc_t is the memory cell which is used to store and access the data signal through hidden layer to next in every iteration. The sigmoid function is applied to the input gate for deciding and updating the signals and output from input gate is combined together to form a new candidate value. At the same time, the value of tanh (sigmoid) also updates in each state layer. The algorithmic procedure of LSTM in a cooperative network of NOMA for the optimised channel estimation is given below:

3.2.1 Algorithm 1 LST Min Cooperative Network for Estimation Channel

The proposed LSTM channel estimation is given by Algorithm 1 below - In the algorithm 1, LSTM model, the input layer, and hidden layer, respectively. In addition, a forget gate, input (update) gate, and output gate are added to each hidden layer. The input gate uses the sigmoid function to decide which values are updated, and the output of the input gate is combined with the new candidate values.

Input: $user_1, user_2, \ldots, user_n$ multi user for transmitting signal in sequence time interval t.

Output: LSTM Network model

Step 1: Generate sequence of input data signal for each user. Initialize iteration $iter = 0$.

Step 2: Randomly initialize the $weight_i$ and b_i as value.

Step 3: In the hidden layer, forget the gate,

$$fg_i = \text{sigmoid}\left(\sum n \,\&\, w_t \,\&\, w_t f_{outt-1} + w_t\, f_{ixt} + biasf\right) \tag{5}$$

Step 4: Input Gate

$$inp_p = \text{sigmoid}\left(\sum n\, wt_i out_{t-1} + wt_i xt + bias_i\right) \tag{6}$$

Step 5: Candidate value of output gate in the hidden layer,

$$candt_t = \tanh\left(\sum nwt_c out_{t-1} + wt_c xt + bias_c\right) \tag{7}$$

Step 6: Update the previous memory cell state, mc_{t-1}, into new cell memory state, mc_t by

$$mc_t = \left(mc_{t-1} \times fg_t\right) + \left(inp_t \times candt_t\right).$$

Step 7: Update the output of LSTM model by using:

Output gate:

$$out_t = \text{sigmoid}\left(\sum_{(\text{iter}=1)}^{n} wt_0 out_{t-1} + wt_0 ix_t + bias_c\right).$$

Estimation of channel condition:

$$out_t = out_t \times \tanh\left(mc_t\right).$$

The out_i of the i^{th} layer can be expressed as

$$out_i = \text{sigmoid}\left(wt_i out_{i-1} + bias_i\right) \tag{8}$$

This procedure is needed to maximize the expressive power of LSTM and it was implemented for n = 2500 iterations. The tanh() function is always used to create the new candidate vector value, and the conditions are added in the LSTM model by

$$\tanh(y) = \left(1 \mp \mathrm{e}^{-2y}\right) / \left(1 + \mathrm{e}^{-2y}\right) \tag{9}$$

It updates the condition of the cell from c and t_{j-1} to c and t_j. In the NOMA model, suppose the data rate is lower than the channel's capacity. Then its signal vector value must be discarded. At the same time, the channel conditions abruptly disturbed then the capacity of the channel will be degraded. That is, some signals should be discarded during the transmission of data signals, and the remaining signals should be included in the model for updating the process. Even though the LSTM model is an efficient one but for the transmission of a sequence of data the cooperative network-based NOMA, the number of users increases and resource sharing produces low performance, a high rate, and to overcome these issues, optimised estimate channel estimation induced with PSO is implemented.

In the Particle Swarm Optimization (PSO), each individual of the population is called a particle which is based on its position of swarm, vector value of velocity and its fitness value.

The position of the particle is y and its velocity vel which are represented as

$$Y_{pos}^{i} = \left[y_{pos}^{1}, y_{pos}^{2}, \dots, y_{pos}^{i} \right] \tag{10}$$

Here pos = 1, 2, …, n represents the dimension of particles. In each iteration, the particles' position changes along with their velocity vel^i. The individual best position of the particle is denoted as $Pbest^i_{pos}$ similarly, the position of the particle globally is denoted as $Gbest^i_{pos}$.

$$Pbest_{pos}^{i} = \left[p_{pos1}^{1}, p_{pos2}^{2}, \dots, p_{posn}^{i} \right] \tag{11}$$

and

$$Gbest_{pos}^{j} = \min\left\{ Pbest_{pos1}^{i}, Pbest_{pos2}^{i}, \dots, Pbest_{posn}^{i} \right\} \tag{12}$$

At the end of each iteration the position and its velocity can be updated based on Eqs. (13) and (14).

$$\begin{aligned} vel_i^{t+1} &= wvel_i^t + coef_1.rnd_1\left(Pbest_i^t - cx_i^t\right) + \\ &+ coef_2.rnd_2\left(Gbest_i^t - cx_i^t\right) \end{aligned} \tag{13}$$

$$cx_i^{t+1} = cx_i^t + vel_i^{t+1} \tag{14}$$

where, i = 1, …, N - no. of swarm population, vel^t - velocity vector, t - iteration, cx^t - current position of an i^{th} particle, $Pbest^t$ - previous best position of the i^{th} particle, $Gbest^t$ - recent current best position of a whole particle, $coef_1$ and $coef_2$ - coefficients called cognitive parameter a social parameter, rnd_1, rnd_2 ∈ [0, 1] - random numbers, w - internal coefficient to control the local and global search. The standard PSO can update the position of the particle by using:

$$x_i \begin{cases} 1 \text{ if } rnd < \text{sigmoid}\left(vel_i^{t+1}\right) \\ 0 \qquad \text{otherwise} \end{cases} \tag{15}$$

where sigmoid(vel_i^{t+1}) is the sigmoid function that will transform the velocity into the range (0, 1), and () - random number selected from the distribution in the range [0, 1].

These values must be updated to their new position based on the best fitness value.

$$fitness = \sum_{n=2}^{n} abs\left(wt_1 Rate_1 - wt_n Rate_n\right) \tag{16}$$

Here, abs() provides the weight wt and $Rate_1$, $Rate_n$ are the strong rate of channel capacity with the weak rate of channel capacity. Each particle's performance is evaluated at the end of the iterations. The objective function of PSO aims to minimise the value of the fitness function to zero. The algorithmic procedure of PSO is given below:

3.2.2 Algorithm 2: PSO for Resource Allocation for Maximin Fairness

The PSO for resource allocation for maximin fairness is given by Algorithm 2. In the algorithm Algorithm2, the multi user in the NOMA model, a resource is allocated to each user in the channel condition based on the power allocation in a channel. PSO is an optimisation technique based on birds' flocking behaviour. A large population (swarm) of candidate solutions (particles) is placed at random initial positions and moved in the search space until the optimal solution is detected.

Input: LSTM Model, Population of user *popu*; iteration number *iter*; Each particle (user) in population y^i_{pos}
Output: Sharing resource and power allocation of particles
Step 1: Initialise the position y^i_{pos} and its velocity vel^i_{pos}
Step 2: While ((i < *iter*) or (*fitness* ≥ ε)) do
Step 3: Evaluate fitness for each particle
Step 4: Update $Pbest^i_{pos}$ value of iteration i using Eq. (11)
Step 5: Update $Gbest^i_{pos}$value of iteration i using Eq. (12)
Step 6: Repeat Step 2 to step 5 until it reaches maximum iteration

Form the particles of the PSO algorithm initially randomly generate the sample users (particles). These randomly generated users are applied in the PSO algorithm for evaluating the best value in both aspects of personally and globally in each iteration. After the completion of all iterations or its convergence the best value globally is taken as an optimal output, for each iteration the fitness value also calculated by using the Eq. (16).

4 SIMULATION RESULTS AND DISCUSSION

In this section, simulations are carried out to execute the performance of the proposed worklist induced with PSO in a cooperative network based on NOMA (LSTM-PSO). MATLABR2018b tool solves the simulation model at Intel i5 3.20GHz processor. In the cooperative network-based NOMA can be simulated from a single base station (BS) and transmits the sequence of data signals. To evaluate the channel estimation by detecting the condition of the channel by using LSTM-PSO. This proposed work evaluates the performance in the aspects of root-mean-square error and loss.

$$RMSE = \sqrt{\ } \left(out_i - out\right)^2 \tag{17}$$

$$Loss = \sum_{i=1}^{n} = \left(out_i - \hat{o}ut_i\right)^2 \tag{18}$$

Here, out_i is the actual output impulse response from channel and $\hat{o}ut_i$ is the predicted output impulse response, N is the number of predictions. Fig. 3 and Fig. 4 show the RMSE and loss evolution using Eqs. (17) and (18).

First, the DNN-UC scheme is simulated with different activation functions to demonstrate their throughput achievements for different numbers of users in the NOMA system. In optimising the algorithm selection of activation, function plays an important role; the LSTM-PSO model uses two variations of activation functions like tanh and sigmoid function.

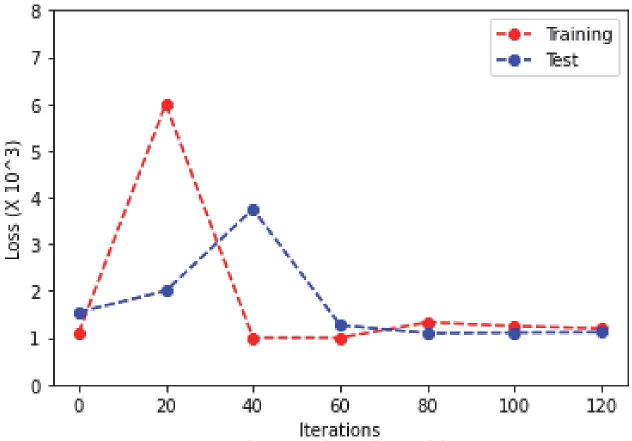

Figure 3 Loss function of the LSTM-PSO model

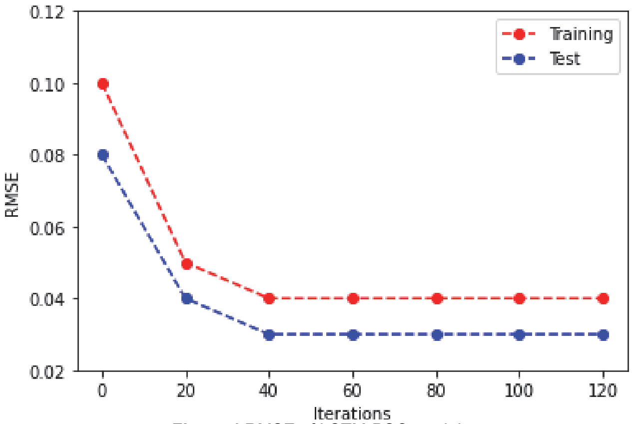

Figure 4 RMSE of LSTM-PSO model

Tab. 1 shows that parametric metric measures, which are used in the LSTM-PSO model for the estimation of channel condition, were tested for about 2500 iterations and its average RMSE is 4.36×10^{-6} and average of Loss is 1.45×10^{-11}.

Table 1 Simulation parameters for LSTM-PSO

Parameter	Value
Number of Layers	4
Input Layer's Number of Neurons/Layers	1200
LSTM model's number of neurons/layer	250
Fully connected layer's Number of neurons/Layer	8
The value of Learning rates are	0.006, 0.0001
Length of Training data	1444 × 1
Length of Testing data	777 × 1
Data Size	2500 × 1
Activation Function	Sigmoid, tanh

But in this work, we implement three variations of activation functions, like sigmoid, tanh and sine for various number of users are shown in Fig. 5.

Fig. 5 shows that the sigmoid function outperforms better results other than the tanh and sine activation functions by 12%, 15%, and 28% in terms of throughput of $K = 30$. The sigmoid function propagates a sequence of input, higher throughput, handling multi-users. But Sine, tanh function produces a poor convergence rate and creates local optima problem. Fig. 6 shows the learning rate of throughput performance in various epochs.

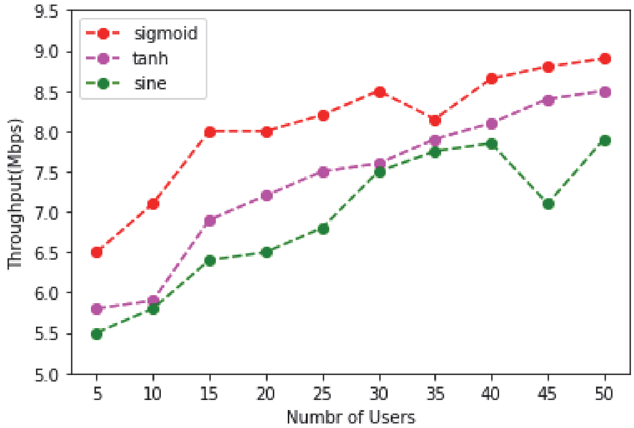

Figure 5 Activation function of LSTM-PSO

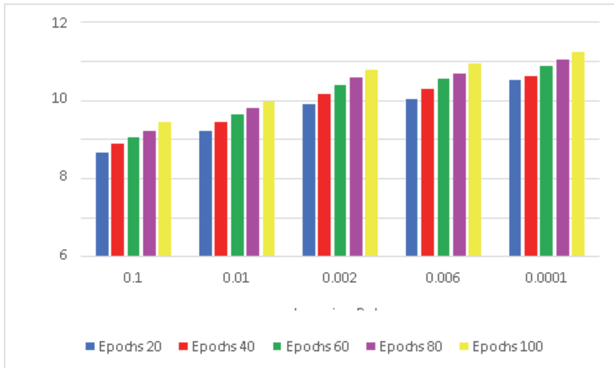

Figure 6 Performance of throughput in various learning rates

Fig. 6 shows that the best performance of throughput (8.2 Mbps) is produced when its learning rate is at 0.0001 in 100 epochs. When the learning rate is low, our model LSTM- PSO requires more epochs of training by adjusting the weight value in the network. Similarly for the high learning rate the throughput gets decreases. In the Fig. 6, the learning rate of 0.1 throughputs of 6.2 Mbps can obtain for the training epochs of 100. Fig. 7 shows that throughput performance is based on the length of sample data with various numbers of users in the NOMA based cooperative network.

In the proposed model of LSTM-PSO, the clustering of users in the NOMA-based cooperative network training the sample data set efficiently with increased users and resources. The power allocation also increases based on the slight increase in users.

Therefore, training the sample data of various variations in length is needed to increase power allocation. In Fig. 7, the LSTM-PSO model uses variations in the length of sample data sizes which are 40000, 50000, 60000 and 70000.

These different training data lengths are implemented in various network sizes at the learning rate value of 0.0001. When the number of users increases with various length sizes, sample data is trained in the cooperative network using different users.

In the observation of Fig. 7, if data size increases, it creates an overfitting problem. If the number of users increases, the bandwidth rate decreases. Therefore, in this proposed work optimised algorithm of PSO is implemented, which solves the overfitting problem and increases the bandwidth.

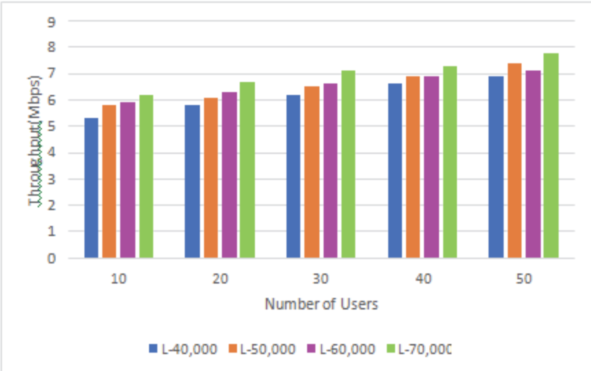

Figure 7 Performance of throughput in various size sample data set

This proposed work obtained the best throughput if it is trained with a large size of file information. Fig. 8 shows that based on the performance of throughput in various algorithms of NOMA-based networks with various numbers of users.

In this comparison, existing algorithms of NOMA network-based LSTM [16], PSO [17], ANN and DNN [15] with the proposed model of LSTM induced with the optimised algorithm of PSO is implemented with various number of users in the network of NOMA with cooperative network.

To analyse the effectiveness of the simulation of various models with the proposed model of LSTM induced with PSO in the cooperative network in the aspect of throughput, performance for various numbers of users is shown in Fig. 8.

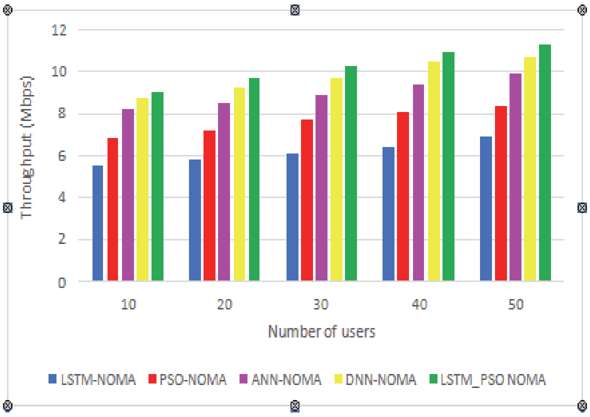

Figure 8 Comparison of various algorithms in the performance of throughput

It seems that more users available in the NOMA-based network produced better results in the throughput performance. LSTM-PSO can outperform DNN-NOMA by 6% to 10% of various users. The structure of the LSTM model provides more hidden layers with forget gate, which produces the optimised result in handling heterogeneous-based users, formation of cluster groups with various users, increased throughput, low latency, estimation of channel conditions and power allocation. Fig. 9 shows the accuracy rate of various algorithms.

It seems that from Fig. 9, our proposed work LSTM-PSO got a higher accuracy rate of 92.05%, LSTM got 86.45%, PSO got 88.13%, and the accuracy rate of ANN and DNN was 83.76% and 84.70%.

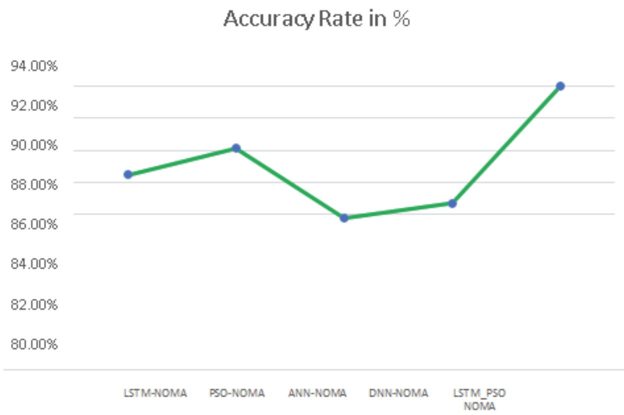

Figure 9 Accuracy

Table 2 Accuracy analysis of the proposed system

Algorithm	Accuracy / %
LSTM-PSO	92.05
PSO	88.13
LSTM	86.45
DNN	84.70
ANN	83.76

5 CONCLUSIONS

In this research work, we presented a new channel estimation technique based on LSTM, aiming to improve the conventional NOMA system's outage probability, BER, and user sum rate. This new power coefficient allocation algorithm divides power among N users according to each user channel condition. To further improve the BER, LSTM induced with optimisation algorithm of PSO in a cooperative network of NOMA model has been proven efficient and feasible for handling the complexity of 5G networks. The inclusion of forget gate in the structure of the LSTM model produces to store and access the last sequence of input with the long-term transmission of data signal based on the time series. The advantage of LSTM-PSO in Cooperative networks is that it provides high performance, better utilisation of downlinks, efficiency in sharing of resources, enhancing the activity of users, capacity of the base station and improving quality of service, estimation of channel condition, efficiency in power allocation. LSTM-PSO got a higher accuracy rate of 92.05%, LSTM got 86.45%, PSO got 88.13%, and the accuracy rate of ANN and DNN was 83.76% and 84.70%. In future work, this work may be extended up to solving reduction in complexity, adopting new deep learning or machine learning technique for channel and data detection efficiently. Hence, we plan to extend the work by investigating interference mitigation techniques among wireless communication technologies.

6 REFERENCES

[1] Jul, J., Zhang, G., Sun, Q., Jin, Li., & Duan, W. (2019). On the performance of receiver strategies for cooperative relaying cellular networks with NOMA. *Journal on Wireless Communications and Networking*, *76*(2019). https://doi.org/10.1186 /s13638-019-1377-5

[2] Gao, X., Liu, Y., Liu, X., & Qin, Z. (2020). Resource Allocation In IRSs Aided MISO-NOMA Networks. *A Machine Learning Approach*. https://doi.org/10.1109/GLOBECOM42002.2020.9348009

[3] Wu, Q. & Zhang, R. (2020). Towards smart and reconfigurable environment. Intelligent-reflecting surface-aided wireless network. *IEEE Communications Magazine*, *58*(1), 106-112. https://doi.org/10.1109/MCOM.001.1900107

[4] Yu, X., Xu, D., & Schober, R. (2019). Enabling secure wireless communications via intelligent reflecting surfaces. *IEEE Global Communications Conference (GLOBECOM)*, *9*(13). https://doi.org/10.1109/GLOBECOM38437.2019.9014322

[5] Huang, H., Xiong, J., Yang, J., Gui, G., & Sari, H. (2017). Rate Region Analysis in a Full-Duplex-Aided Cooperative Nonorthogonal. *Multiple-Access System*, *5*, 17869- 17880. https://doi.org/10.1109/ACCESS.2017.2747129

[6] Yu, X., Yang, F., Yun, J., & Wu, S. (2022). CIRNN: An Ultra-Wideband Non-Line-of-Sight Signal Classifier Based on Deep-Learning. *Tehnicki Vjesnik*, *29*(4), 1139-1147. https://doi.org/10.17559/TV-20220315024522

[7] Wei, Z., Ng, D. W. K., Yuan, J., & Wang, H. M. (2017). Optimal Resource Allocation for Power-EfficientMC-NOMA With Imperfect Channel State Information. *IEEE Transactions on Communications*, *65*(9), 39443961. https://doi.org/10.1109/TCOMM.2017.2709301

[8] Yang, L., Chen, J., Ni, Q., Shi, J., & Xue, X. (2017). NOMA-Enabled CooperativeUnicast-Multicast: Design and Outage Analysis. *IEEE Transactions on Wireless Communications*, *99*, 1-1.

[9] Oviedo, J. A. & Sadjadpour, H. R. (2017). A Fair Power Allocation Approach to NOMA in Multiuser SISO Systems. *IEEE Transactions on Vehicular Technology*, *66*(9), 7974-7985. https://doi.org/10.1109/TVT.2017.2689000

[10] Liaqat, M., Noordin, K. A., Latef, T. A., & Dimyati, K. (2018). Power-domain non-orthogonal multiple access (PD-NOMA) in cooperative networks: an overview. *Wireless Networks*, *26*, 181-203. https://doi.org/10.1007/s11276-018-1807-z

[11] Hussain, M. & Rasheed, H. (2020). Nonorthogonal Multiple Access for Next-Generation Mobile Networks. A technical Aspect for Research Direction. *Wireless Communications and Mobile Computing*, *5*, 1-17. https://doi.org/10.1155/2020/8845371

[12] Mu, X., Liu, Y., Guo, l., J. Lin., & Dhahir, N. A. (2019). Exploiting intelligent, reflective surfaces in multi-antenna-aided NOMA systems. *IEEE Transactions on Wireless Communications*, *19*(10), 6884-6898. https://doi.org/10.1109/TWC.2020.3006915

[13] Fu, M., Zhou, Y., & Shi, Y. (2019). Intelligent reflecting surface for downlink nonorthogonal multiple access networks. *2019 IEEE Globecom Workshops*. https://doi.org/10.1109/GCWkshps45667.2019.9024675

[14] Liu, X., Y., Chen, Y., & Poor, H. V. (2020). RIS enhanced massive nonorthogonal multiple access networks: deployment and passive beamforming design. *IEEE Journal on Selected Areas in Communications*, *PP*(99), 1-1.

[15] Kumaresan, S. P., Tan, C. K., & Ng, Y. H. (2021). Deep Neural Network (DNN) for Efficient User Clustering and power allocation in Downlink Non-Orthogonal Multiple Access (NOMA) 5G Networks. *Symmetry*, *13*, 1507. https://doi.org/10.3390/sym13081507

[16] Abdel Moniem, M., Gasser Mahallawy, S. M., M. S. E. M., WaleedFakhr, M., & Soliman, A. (2019). Enhanced NOMA System Using Adaptive Coding and Modulation Based on LSTM Neural Network Channel Estimation. Applied Sciences, *9*(15), 3022. https://doi.org/10.3390/app9153022

[17] Dhakal, D.R., Pan, Z., Saito, M., & Shimamoto, S. (2020). Dynamic Resource Allocation in Nonorthogonal Multiple Access Using Weighted Maximin Fairness Strategy for a UAV Network. *Journal of Signal Processing Systems*, *92*, 1397-1406. https://doi.org/ 10.1007/ s11265-020-01565-8

[18] Ding, L., Jiayi, C., Zhuo, W., & Yuehui, S. (2023). LSTM Deep Neural Network Based Power Data Credit Tagging Technologyy. *Technical Gazette*, *30*(1), 324-334. https://doi.org/10.17559/TV-20220628151845

[19] Jayamathi, A., Jayasankar, T., & Vinoth Kumar, K. (2022). Novel Selective Mapping with Oppositional Hosted Cuckoo Optimization Algorithm for PAPR Reduction in 5G UFMC Systems. *Technical Gazette*, *28*(2), 464-471. https://doi.org/10.17559/TV- 20210524085655

Contact information:

Kavitha GOPALUN, Research Scholar
(Corresponding author)
Department of Electronics and Communication Engineering,
Kalasalingam Academy of Research and Education,
Krishnankoil - 626126
E-mail: hodbme@aec.org.in

Dr Deny John SAMUVEL, Associate Professor
Department of Electronics and Communication Engineering,
Kalasalingam Academy of Research and Education,
Krishnankoil - 626126
E-mail: j.deny@klu.ac.in