Tuijin Jishu/Journal of Propulsion Technology
ISSN:1001-4055
Vol. 44 No. 3 (2023)

Signal Identification in Non-Orthogonal Multiple Access Wireless Systems Using Bi-Directional Long Short-Term Memory Network

Neeraj Dwivedi[1], Sachin Kumar[1], Sudeep Tanwar[2], Sudhanshu Tyagi[3]

[1]*Research Scholar, Amity University, Lucknow Camo,*

[2]*Institute of Technology, Nirma University, Gujrat,*

[3]*Thapar Institute of Engg. And Technology, deemed to be University, Punjab*

Abstract

This study's goal is to provide an early analysis of deep learning (DL) for signal identification in wireless systems that use non-orthogonal multiple access (NOMA). The successive interference cancellation (SIC) approach is frequently used at the receiver in NOMA systems when several users are decoded successively. Without explicitly calculating channels, a DL-based NOMA receiver can decode messages for several users at once. To estimate the multiuser uplink channel (CE) and recognize the initial broadcast signal in this study, it is recommended that a deep neural network with bi-directional long short-term memory (Bi-LSTM) be utilized. The suggested Bi-LSTM model, in contrast to conventional CE techniques, may immediately retrieve transmission signals impacted by channel distortion. During the offline training phase, the Bi-LTSM model is trained using simulation data based on channel statistics. The trained model is then applied to retrieve the transmitted symbols in the stage of online deployment. According to the findings, the DL method could outperform a maximum probability detector that considers interference effects when inter-symbol interference is substantial.

Keywords*-NOMA, Deep learning, signal detection, wireless communication, Bi-LSTM*

1. Introduction

Cellular networks are getting denser and more complexsince of the rising demand for wireless services that can achieve exceptionally high speeds while maintaining a low level of latency. The creation and management of cellular networks that have a large number of components and features is one of the most significant tests that operators of cellular networks face. As a direct result of this, self-organizing networks, also known as SONs, have developed into essential elements in the management of wireless cellular networks[1]. SON technology mains to decrease capital and operational expenses by reducing the amount of human participation required in a network via the use of multiple capabilities. These capabilities include self-healing, self-optimization, and self-configuration. The prevention of cell failures is an important application for self-healing technology. It pertains to base stations (BSs) that experience a coverage gap in the network because they are unable to continue offering services to customers who are present in their service area [3][25].

Cellular networks are using a wide variety of accessing approaches, with as FDMA, TDMA, CDMA, and OFDMA, to expand coverage and throughput. These accessing strategies take advantage of the idea of orthogonality to lessen the likelihood of interference between users; however, this also has the effect of lowering the total number of users who are multiplexed to access the spectrum[4]. By permitting more users than the available orthogonal resources can handle, NOMA has developed into a viable alternative in 5G networks for increasing the spectral efficiency (SE) of networks and the capacity of cell-edge users. In the powerdomain, NOMA makes advantage of fresh user multiplexing strategies that were underutilized in earlier generations. A sequential interference canceller (SIC) is used to de-multiplex users on the receiver side after multiplexing them in the power domain of NOMA [5][6].

The 5G wireless network, which is the next generation of wireless communication, provides greater QoS and higher capacity for applications employed by current wireless networks. It also enables exceptionally fast data rates and extremely low latency[7]. Multipath delay spread and Doppler shift is two factors that contribute to frequency selective fading in the channel of a wireless communication system. The modeling of the time-varying wireless channel is an essential part of the processin 5G wireless communication systems [8].The LSTM kind of deep learning architecture was investigated to identify and forecast time series events that had varying lengths of time delays between them[9]. To fix the problems with the LSTM, a Bidirectional LSTM has been included in the system. A specified time frame is used to train the model utilizing input data sequences from both the past and the future of that time frame[10]. Moreover, [29] have shed light on the difficulty of training deep feedforward neural networks, which is relevant to the challenges faced in optimizing certain deep learning architectures."

1.1 NOMA scheme based on power domain division

In NOMA, multiple users' signals can be superimposed on top of one another. Sharing the same radio resources across numerous user equipment (UEs) might lead to an increase in capacity or throughput in NOMA, as demonstrated in Figure 5a and Figure 5b. This can be predicted to boost capacity or throughput. The provision of service to users located in the cell center as well as at the cell edge is an example of a common NOMA application scenario[11]. Because of the relatively low route loss experienced by users near the cell center, this user's signal is the one that is identified first during the process of signal detection. Meanwhile, the signal of users at the cell edge is considered to be interference. In the process of detecting the signal of a user at the cell edge, the signal of a user in the cell center is first recognized and decoded. After that, the received signal is processed to remove the user's signal from the cell center, and the user's signal from the cell edge is discovered, found, and decoded [12].

The primary benefit of NOMA is that it is possible to schedule a cell center user and a cell edge user to achieve great performance with very minimal processing cost (the SIC detector is always used). It's also simple to get a use rate of 200 percent. The biggest drawback of NOMA is the limitations it places on users who must adhere to fixed time slots. Users in the cell's core and its periphery should typically share the same resource block. One user's SNR is guaranteed to be poor owing to interference from the other user's signal when a SIC type receiver is applied to a system with two users scheduled at the cell center or the cell edge. The NOMA was first conceived as an eMBB device[13]. When applied to mMTC, the result would be a low received SNR and a small number of users (only two or three users might share a block of resources, compared to many more in other non-orthogonal multiple access systems) [26]. Estimating the channels used by consumers requires either further pilots or a lengthy introduction.

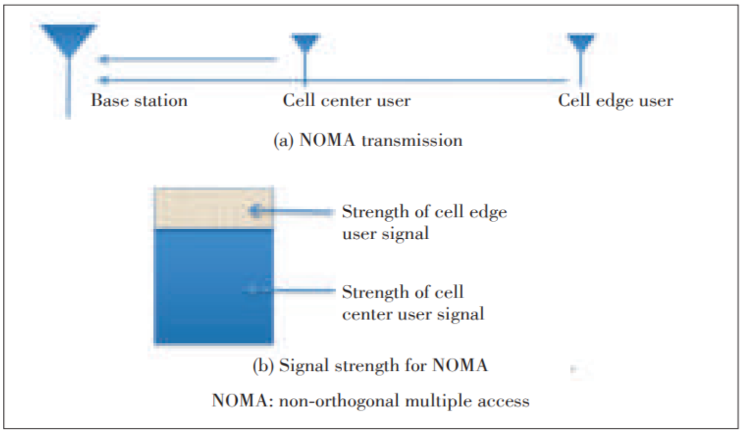


Figure 1.Block diagram of NOMA[14].

2. Review of literature

The author examined thatin milling, surface roughness, and machining precision are crucial quality indicators. Recent developments in sensor technology and data processing have made it possible to utilize cutting force signals gathered during machining to forecast and quantify machining quality. Artificial neural networks (ANNs) trained with deep learning can analyze and conclude massive amounts of signal data. On the other hand, the whole-data training showed that the deep neural network (DNN) model had an error rate of over 50%, while the CNN and LSTM models only had an error rate of 20%. Predictions of machining accuracy using DNN and CNN models trained on the whole dataset were within 10% of the true value, whereas predictions using the LSTM model had an error of up to 20%. The outcomes of the categorization training, however, did not increase much. Concerning analytical efficiency across all training processes, the CNN model came out on top, followed closely by the LSTM model [15].

The author developing sound communication systems in an underwater acoustic environment (UWA) is still difficult for researchers. The communications system is complicated because these acoustic channels have unfavorable characteristics including a significant propagation latency and erratic Doppler shifts. The hybrid combining of the CNN and ensemble single feedforward layers (SFL) is used in this research to present a unique intelligent selection approach between the various modulation schemes, such as CDMA, TDMA, and OFDM. The channel characteristics are extracted using CNN, and the modulation is chosen based on the CNN outputs using boosted ensembled feed-forward layers. The full experiment is conducted and different hybrid learning models and conventional techniques are examined. The results of simulations show that the suggested hybrid learning models outperformed the other models in implementing the communications schemes under dynamic underwater conditions, reaching approximately 98% accuracy and a 30% increase in BER performance [16].

The author looked at the performance of LSTM-based DL NOMA receivers in the presence of Rayleigh fading channels. We compare the DL-based NOMA detector's performance to that of the traditional NOMA technique, and the results show that it performs significantly better. After accounting for all plausible conditions except for the cyclic prefix (CP) and clipping distortion, we compare the performance of the DL detector to that of the simulated curves in terms of MMSE and the least square error (LSE) estimate. The simulation curves demonstrate that the detector's accuracy performs admirably when it reaches 1 when the SNR is higher than 15 dB, assuming that the DL technique is more robust to clipping distortion [17].

The authoranalyzed thatuniversal filtered multicarrier (UFMC) has become a viable rival for OFDM for wireless systems in the 5G and beyond. In this research, we suggest a detector for the UFMC system that is based on Bi-LSTM. The suggested detector employs DL-based training data to directly detect conveyed symbols. The system is initially provided with the use of pilot symbols and training data. The DL-based network factors are tuned during training. The trained network is used to identify the signal during the testing phase. The suggested scheme's performance has been contrasted to that of the DL-assisted OFDM system and to signal detection methods that employ traditional channel estimate techniques. The experiments demonstrate the flexibility and efficiency of the suggested Bi-LSTM-based DL in detecting UFMC signals [18].

The author examined two emerging approaches to tackling time series prediction issues machine learning- and deep learning-based algorithms. It has been discovered that these methods produce more accurate results than conventional regression-based modeling. In OFDM-NOMA, a method for signal detection with deep learning is provided. Different deep learning-based optimization techniques like Sgdm, RMSprop, and Adam are used to detect signals using the DNN with a Bi-LSTM. A comparison of neural networks and optimizers identifies the most accurate detection combination. The simulations indicate that the Bi-LSTM-based DL approach may successfully detect signals in NOMA system situations in the LSTM model and that it may outperform the standard SIC approach. Consequently, DL is a trustworthy and crucial technique for identifying NOMA signals [19].

The author focused on the v2v dynamic channel in tactical interactions, which exhibits time-varying and nonstationary features because of the quick movement, directional antennas, and difficult terrain. We suggest a CSI predictor based on the LSTM network to get an accurate CSI and decrease pilot overhead. The addition of the gating mechanism to LSTM units results in an enhanced RNN that has outstanding learning performance on both long- and short-term inputs. Results from simulations support the usefulness of the LSTM-based predictor in comparison to conventional IEEE 802.11p approaches. Further analysis is done on the important variables that have an impact on the proposed predictor's performance [20].

The author analyzed thatdue to the rapidly increasing wireless capacity demands imposed by enhanced multimedia apps and the significantly growing demand for user access necessary for the IoT, the 5G networks have trouble managing large-scale heterogeneous data traffic.When compared to traditional OMA techniques, this results in a significant increase in bandwidth efficiency. Many researchers were inspired to devote significant research resources to this area as a result. In contrast to other NOMA approaches already in use, we emphasize the key benefits of power-domain multiplexing NOMA. We give possible remedies as well as a summary of the difficulties with the NOMA's current research activities. We conclude by providing some design recommendations for NOMA systems and pointing out potential future research directions [21].

The author studied that the primary focus of this paper is the analysis of the implementation of NOMA systems on SDR platforms since NOMA has been identified as a key allowing technology for the 5G wireless networks. This report provides a thorough analysis of NOMA's historical development as well as the most recent trends and potential future research initiatives. OMA and NOMA system performance is also contrasted in terms of rate pairs (throughput), and spectrum efficiency. The conclusion is that the NOMA system outperforms OMA solutions, and it will be emphasized that SDR is a versatile platform for implementing and testing future wireless innovations [22].

The author stated that UAVs have recently attracted a great deal of interest for a variety of uses, including wireless protection, surveillance flights, precision agriculture, development, power line tracking, and blood supply, among others. The UAV's inherent characteristics, such as rapid deployment, swift mobility, increased flight length, advances in payload capacities, etc., make it a strong option for a variety of applications in 5G and Beyond communications. To increase system efficiency, we build a review in this article to look into the UAVs' joint optimization challenges. We also examine the effects of AI, ML, DRL, MEC, and SDN on joint optimization issues involving UAVs and give difficulties and ideas for further study [23].

The authorprovided a ground-breaking solution to the issues of user grouping and power allocation in this workusing NOMA systems. First, users must be gathered and assigned to the predetermined periods. The answer regarding how much electricity should be given to the various consumers is provided in the second step that comes after this. By attempting to solve the partitioning step of this problem, we find a solution with the first Reinforcement Learning (RL)-based method that has been published. To handle the user grouping issue for NOMA systems in stochastic situations, we specifically employ the Object Migration Automata (OMA) and one of its versions. Then, based on a greedy heuristic, we infer the power allocation using the ensuing groupings. The simulation findings show that our method is capable of precisely and quickly resolving the issue [24].

3. Problem formulation

NOMA has been identified as viable multiple-access technology in 5G wireless networks for enhancing spectrum efficiency and system performance. By multiplexing users in the power or code domains, NOMA gives many users coordinated access to the same frequency resources [1]. In OFDM systems, one user has access to a set of subcarrier channels within a single time slot. By putting the NOMA concept into practice, the bandwidth resources may be efficiently utilized by sharing the subcarriers sent to a user with poor channel conditions with a user with outstanding channel conditions. Since the receiver will receive a superposition of signals from many users, inter-user interference must be reduced to successfully decode NOMA systems. Through SIC in the power domain, contemporary multi-user detection (MUD) in NOMA is accomplished. Finally, using CSI, messages from multiple users are decoded in decreasing order of signal strength [2]. The potential for pilot symbols used for channel estimation [27]to interfere with signals from other users makes the collection of CSI in NOMA challenging. As a result, methods for estimating conventional channel parameters like least square (LS) and MMSE estimations may perform substantially less well. In [3], a novel power allocation and channel estimate strategy for a two-user NOMA system is put forth, where a minimal SINR for the weak user is guaranteed while the average effective signal-to-noise-plus-interference (SINR) for the strong user is maximized. Nevertheless, the suggested method is for narrowband channels. For time-dispersive channels, the computational difficulty may grow.

4. Research Methodology

As seen in Figure 2, a two-user uplink NOMA scenario in an OFDM system is explored in this section. In this instance, the two user terminals exchange data simultaneously by using the same frequency resources. Two users' superimposed data symbols, together with channel noise, will be sent to the base station (BS). Both the BS and the user terminal make use of the same antenna.

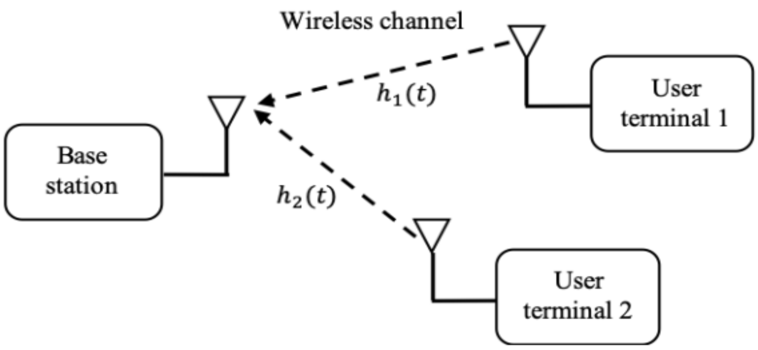


Figure 2. Two-user NOMA system

The assumption used in the power distribution is that the transmitter and receiver are both aware of the CSI. The purpose of power sharing is to provide a range of users with anappropriate SINR used at the receiver for joint decoding. The received signal on subcarrier k in an N-subcarrier OFDM system with " users per subcarrier is given by the equation below,

$$Y(k) = \sum_{i=1}^{M} \sqrt{pi(k)}\, Hi\ (k) Xi(k) + W(k) \quad (1)$$

Where Y (k), Xi (k), and W (k) represent the additive white Gaussian noise, the user i's broadcast symbol, and the frequency-domain received signal. The transmission power allotted to the user I on subcarrier k is represented by the variable Pi(k). Each of the N subcarriersis allocated total power P and the power allocation coefficient for user i is $ai(k) = \frac{pi(k)}{p}$, which is constrained to have $\sum_{i=1}^{M} ai(k) = 1$.The scalar Hi(t) is the impulse response of a multi-path channel, and Hi(k) is the discrete Fourier transform (DFT) of this response,

$$hi(t) = \sum_{l=1}^{L} \rho_{i,l} \delta(t - \tau_{i,l}) \qquad (2)$$

where $\rho_{i,l}$ and $\tau_{i,l}$ are the complex channel gain and the corresponding time delay of the lth multipath component for user I?Each tap of the single-input and single-output (SISO) channel, which has a total of 20 specified pathways L, is represented by Rayleigh fading.

5. Proposed model

This portion of the paper discusses the recommended "Bi-LSTM model input data preparation, model structure, and operation inside the NOMA OFDM" architecture. Next, the trained model’s online and offlinetesting processes are discussed below.

5.1 Data generation

The 64 subcarrier OFDM is taken into consideration in this work. One data symbol and two pilots make up each OFDM packet. Each symbol in the quadrature phase shift-keying (QPSK) modulation comprises two bits per subcarrier. To prevent inter-symbol interference, the OFDM packet is broadcast across the Rayleigh channel following the IDFT and a guard period of CP data. The multiuser sends the OFDM packet total to the BS, who then gets it with noise. By generating a feature vector (yu) from the received OFDM packet, a sample of training data is kept. All of the symbols in the OFDM packet's real and imaginary values are combined to create the feature vector yu. the number of labels and the number of total data packetsis multiplied to create the total training sample. By employing the matching B(f) in the training, the model may be taught to recover data on any subcarrier f. The number of features in each training sample makes up the feature vector's dimension. The total number of features in this study is 64 x 3 x 2 = 384 with 64 subcarriers and 3 OFDM symbols.

5.2 Model Architecture

5.2.1 Network Description

The LSTM network's forward and reverse directions make up the Bi-LSTM. It can make utilizedata from both sides since the input flows both ways, as seen in Figure 3 (a). Two cyclic neural networks make up the forward and backward layers, which can concurrently connect the output layers. Every point's before and after sequence information may be obtained through the output. Additionally, it investigates how they relate to one another through training. This operation can increase the accuracy of CE. For CE and signal detection, a particular kind of recurrent neural network composed of a series of LSTM cells is utilized, called the directed LSTM. The LSTM network is composed of four layers: "LSTM hidden layers, fully connected layers, softmax function layers, and classification layers." 100 hidden units are required to implement the LSTM hidden layer. The learnable weights in the LSTM hidden layers contain the input weights w. The bias is b, and the recurring weights are T. There are 16 classes in the second tier, which is entirely linked with a fully connected layer.

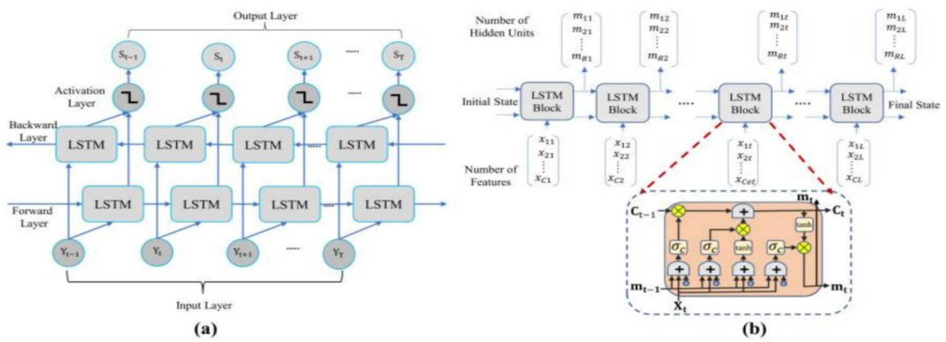


Figure 3 (a) The architecture of the Bi-LSTM model system with its different layers. (b) The internal cell structure of the LSTM model.

The fully linked layer is developed to organize and time-series data for categorization. The fully linked layer processes the LSTM layer output. Before adding a bias vector b, a fully linked layer multiplies the input by a weight matrix w. As a result, it analyses every component of each UE's complex modulated signal. The neurons in the layer with complete connectivity are all linked to the neurons in the layer below. All the characteristics and data gathered from the preceding layer are combined. The fully connected layer in the LSTM network uniquely manages each time step. The softmax activation function is utilized to create the outputs for the terminal layer. The last layer's vector probability receives the output from the classification layer. The error between" them is then provided as training feedback after the building of a completely connected layer with an output size equal to the number of classes. The final formulation is as follows: "mean-squared error (MSE) for the whole network to detect at UEi:

$$MSE = \frac{1}{Q}\sum_{q=1}^{Q}(Si(q) - \hat{S}_i(q))^2 \quad (3)$$

Where the number of training OFDM samples is represented by Q, and Si (q) is the target output, $\hat{S}_i(q)$ is the predicted output at the response q? The standard Adam optimization approach is used to minimize the loss.

5.2.2 The internal structure of LSTM

When learning between time steps of sequence data, the "LSTM network can retain pertinent information. In the OFDM system, the time steps are preserved equally for all subcarriers. The LSTM layer's single time-step module may be used to narrow the DNN's focus and enable multiuser detection for every given subcarrier. Figure 3(b) depicts the internal cell structure and functionality of the LSTM network. The previous cell state and the current input are combined to create the LSTM cell's output.The input gate, forget gate and output gate are the three gates that make up an LSTM cell. Figure 3(b) shows the relationships between the variables t, xt, and mt at a given time t. t stands for the time instant, mt stands for the multiuser current output channel coefficient and xt, the current input. The LSTM cell can enhance or eliminate data from the cell state at each time step; the gate action updates the cell state. The operation of each gate is summarized below:

The forget gate regulates the degree of the cell state that needs to be reset. These words can be used to express the for gate frt:

$$frt = f_{\sigma c}\,(w_{fr}\,xt + T_{fr}\,m_{t-1} + bfr) \quad (4)$$

Wherethe forget gate has a bfr bias, and wfr is the weight related to xt. The input gate controls the level of the cell state that has to be efficient. The following is an expression for the input gate int:

$$int = f_{\sigma c}\,(w_{in}\,xt + T_{in}\,m_{t-1} + bin) \quad (5)$$

Where Tin is the weight related to m_{t-1}, and win is the weight related to xt.The input gate's bias is a bin. The candidate gate controls how information is added to the cell state. The following is one way to convey the candidate gate cat:

$$cat = f_{tan\,h}(w_{ca}\,xt + T_{ca}\,m_{t-1} + bca \quad (6)$$

Where Tca is the weight related to m_{t-1}, and wca is the weight associated with xt. The bias of the candidate gate is bca.

5.2.3 Offline training and online testing operation of the model

Figure 4 illustrates how the offline portion of the training process is taken using the generated data and the suggested model.

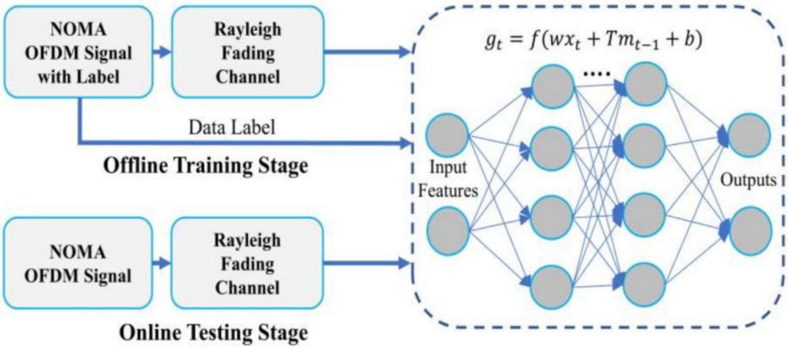


Figure 4.Training and testing process of the proposed model.

The NOMA-OFDM signal is merged with the input from the "model training system" as an input layer to aid the DNN in improving the parameters. As supervised data, equivalent labels are used. Algorithm 1 provides a summary of the proposed model's training procedure.

Algorithm 1 Bi-LSTM training process

1: Load the training and validation data samples.

2: Initialize model parameters such as minibatch size, maximum epochs, and learning rate.

3: Train the model network according to and calculate the accuracy error by equation (3)

4: Adam optimization algorithm is used to compute the corrective parameters and to search for the optimal solution with an update of the parameters.

5: Result: Trained model

6: Save the model.

5.2.4 Testing process

Following repeated training of the suggested method, the online training procedure is taken. Figure 4 displays the dataset-based testing procedure for the proposed model.

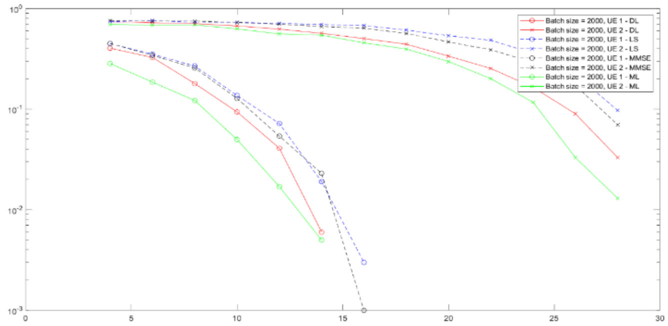
6. Result and discussion

In this portion, the suggested Bi-LSTM and signal detection model in the NOMA-OFDM system simulation results are described in detail. Using the simulation parameter, the suggested Bi-LSTM model and signal detection is simulated.

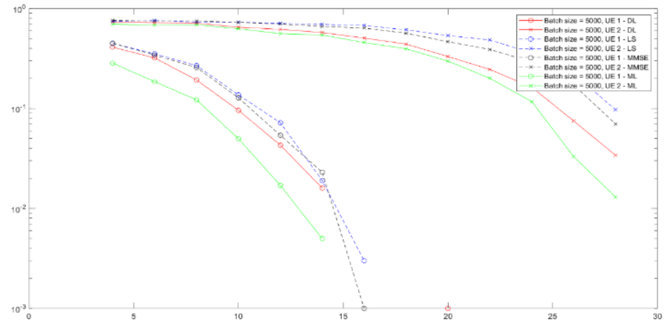
- **Impact size**

The training data is divided into batches, each of which has a significantly lower size than the whole quantity of training samples. Iteration refers to the procedure of one batch moving the DNN in a forward and backward pass. Figure 5depict the symbol error rate (SER) value of DNN trained withseveral batch size such as 2000, 5000, and 20000 as shown below. The DNN will use batches of training data so that less memory is used for each propagation. The impact of various batch sizes is shown in Fig. 5(a), which illustrates that the "larger the batch and Fig.5(b) obtained the larger batch while 5(c) obtained a much larger batch which is the better performance the DNN" can be produced. To achieve the same validation accuracy during the training phase, smaller batches converge more quickly than bigger batches. Smaller batches display a lower testing precision.Although batches need fewer DNN parameter updates and iterations, more data is needed to produce a more precise estimation of the gradient for each update. Therefore, compared to other batch sizes, a larger batch size produces a final receiver with greater efficiency.

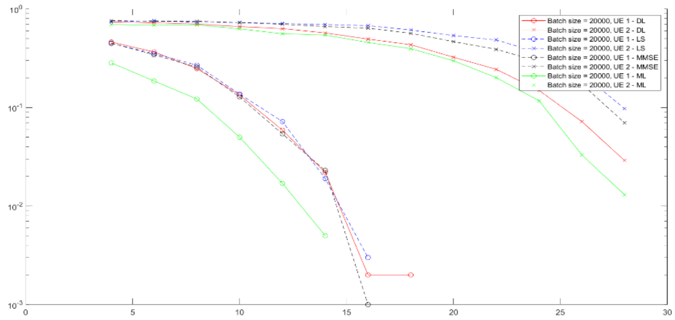
Tuijin Jishu/Journal of Propulsion Technology
ISSN:1001-4055
Vol. 44 No. 3 (2023)



(a)



(b)

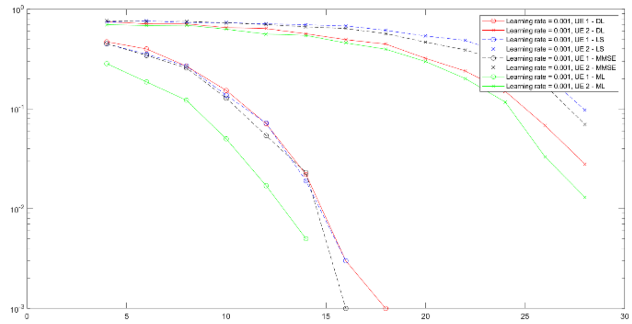


(c)

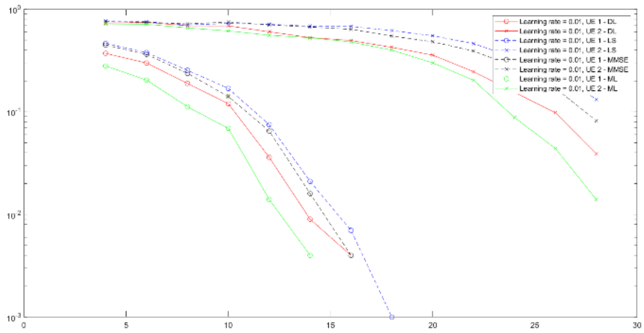
Figure 5 (a). SER value of DNN trained with batch size = 2000 (b) batch size = 5000, and (c) batch size = 20000.

- **Impact of learning rate**

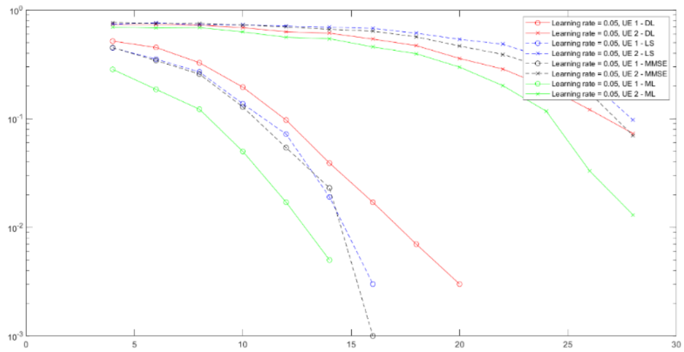
Figure 6 illustrate the SER values of DNN trained with different learning rate such as 0.001, 0.01, and 0.05 as shown below.SER curves for both users are shown in Fig. 6, along with an analysis of the effectiveness of the DL receiver trained at numerous learning rates. The correctness that a greater learning rate would result in more frequent changes to the DNN's weights and a larger validation error is validated by the fact that in Fig. 6, a lower learning rate correlates to a lower SER. A sluggish convergence is caused because many updates are required, even when a lower learning rate, like 0.001, leads to improved accuracy. For all other simulation situations, the learning rate has been changed to 0.01 to take into account a trade-off between training accuracy and training length.



(a)



(b)



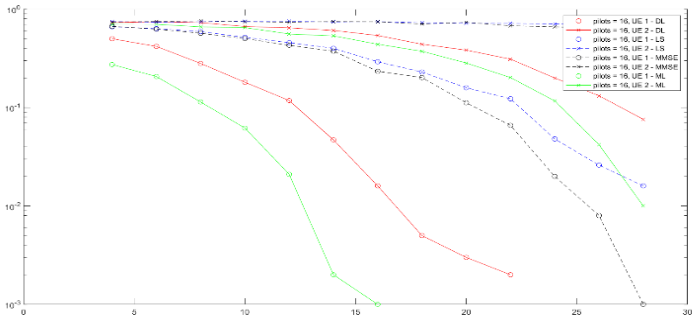
(c)

Figure 6 (a). SER values of DNN trained with learning rate = 0.001, (b) learning rate = 0.01, and (c) learning rate = 0.05.

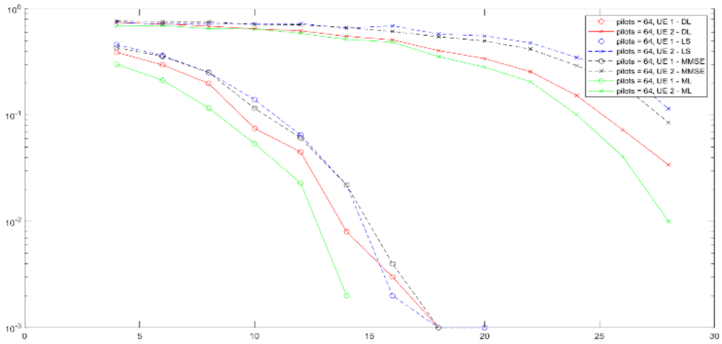
- **Impact of the number of pilot symbols**

Figure 7 depict the SER values of DNN trained with different pilot such as 16 and 64 as shown below. Pilot symbols, which are utilized to recover channel response and are known to the receiver, are crucial to the success of LS and MMSE channel estimations. For the DL receiver, the impact of the pilot symbol count is examined. Each pilot sequence in the simulation consists of 64 or 16 pilot symbols. The SER curves of both examples for Users 1 and 2 are shown in Figs. 7(a) and (b), respectively. According to Figs. 7(a) and 7(b), both LS and MMSE approaches can produce accurate evaluations when 64 pilot symbols are employed. However, the DL receiver can perform more effectively. When the number of pilot symbols is reduced to 16, the accuracy of the LS and MMSE algorithms suggestively declines at "28 dB SNR for both User 1 and User 2. The DL receiver's ability to continue to provide performance equivalent to the 64-pilot scenario shows that the DNN is more robust to the number of pilot symbols and can achieve higher performance with fewer pilots.

Tuijin Jishu/Journal of Propulsion Technology
ISSN:1001-4055
Vol. 44 No. 3 (2023)



(a)



(b)

Figure 7 (a) SER values of DNN trained with pilot = 16 (b) pilot = 64.

7. Conclusion and future scope

This work proposes a signal detection scheme based on the Bi-LSTM model for the NOMA-OFDM system [28]. The suggested model offers improved performance for CE and signal identification when compared to conventional SIC systems. The suggested Bi-LSTM network is more reliable in terms of signal recovery than the traditional CE approaches like MMSE, LS, and ML. According to the simulation findings, the DL method outperforms in comparison to classic channel estimation techniques,and the SIC receiveris more resistant to finite radio resources like pilot symbols, cyclic prefixes, and signal power. For increasingly complicated system models, such as MIMO systems, further analysis, and testing will be done. The starting point for this study's training and testing procedures is a static channel profile. Additionally, the optimization method used for training the Bi-LSTM network is based on the Adam algorithm [30], which has shown promising results in stochastic optimization tasks."

Acknowledgment:

Authors'contributions All authors are equally contributed.

Funding The author declares there is no funding available.

Data Availability Alldataareavailableuponrequestfromthecorrespondingauthor.

Declarations

Conflict of interest Theauthorshavenorelevantfinancialornon-financialintereststodisclose.

Competing Statement The author declares there is no competing interest.

References

[1] 3GPP. Telecommunication Management; Self-Organizing Networks (SON): Concepts and Requirements; 3GPP TS 32.500 V8.0.0; December 2008. Available online: https://www.arib.or.jp/english/html/overview/doc/STD-T63v9_20/5_Appendix/Rel8/32/32500-800.pdf (accessed on 20 November 2022).

[2] Aliu, Osianoh Glenn, Ali Imran, Muhammad Ali Imran, and Barry Evans. "A survey of self-organization in future cellular networks." *IEEE Communications Surveys & Tutorials* 15, no. 1 (2012): 336-361.

[3] Islam, SM Riazul, Nurilla Avazov, Octavia A. Dobre, and Kyung-Sup Kwak. "Power-domain non-orthogonal multiple access (NOMA) in 5G systems: Potentials and challenges." *IEEE Communications Surveys & Tutorials* 19, no. 2 (2016): 721-742.

[4] Vaezpour, Elaheh, Layla Majzoobi, Mohammad Akbari, Saeedeh Parsaeefard, and Halim Yanikomeroglu. "A deep learning-based approach for cell outage compensation in NOMA networks." *IEEE Open Journal of Vehicular Technology* 3 (2022): 149-166.

[5] Benjebbour, Anass, Yuya Saito, Yoshihisa Kishiyama, Anxin Li, Atsushi Harada, and Takehiro Nakamura. "Concept and practical considerations of non-orthogonal multiple access (NOMA) for future radio access." In *2013 International Symposium on Intelligent Signal Processing and Communication Systems*, pp. 770-774. IEEE, 2013.

[6] Saito, Yuya, Yoshihisa Kishiyama, Anass Benjebbour, Takehiro Nakamura, Anxin Li, and Kenichi Higuchi. "Non-orthogonal multiple access (NOMA) for cellular future radio access." In *2013 IEEE 77th vehicular technology conference (VTC Spring)*, pp. 1-5. IEEE, 2013.

[7] Agiwal, Mamta, Abhishek Roy, and Navrati Saxena. "Next generation 5G wireless networks: A comprehensive survey." *IEEE Communications Surveys & Tutorials* 18, no. 3 (2016): 1617-1655.

[8] Sun, Shu, Theodore S. Rappaport, Mansoor Shafi, Pan Tang, Jianhua Zhang, and Peter J. Smith. "Propagation models and performance evaluation for 5G millimeter-wave bands." *IEEE Transactions on Vehicular Technology* 67, no. 9 (2018): 8422-8439.

[9] Maimó, L. F., and Á. Gómez. "LP, Clemente FJG, Pérez MG, Pérez GM." *A self-adaptive deep learning-based system for anomaly detection in 5G networks, IEEE Access* 6 (2018): 7700-7712.

[10] Le, Ha An, Trinh Van Chien, Tien Hoa Nguyen, Hyunseung Choo, and Van Duc Nguyen. "Machine learning-based 5G-and-beyond channel estimation for MIMO-OFDM communication systems." *Sensors* 21, no. 14 (2021): 4861.

[11] Dai, Linglong, Bichai Wang, Yifei Yuan, Shuangfeng Han, I. Chih-Lin, and Zhaocheng Wang. "Non-orthogonal multiple access for 5G: solutions, challenges, opportunities, and future research trends." *IEEE Communications Magazine* 53, no. 9 (2015): 74-81.

[12] Islam, SM Riazul, Nurilla Avazov, Octavia A. Dobre, and Kyung-Sup Kwak. "Power-domain non-orthogonal multiple access (NOMA) in 5G systems: Potentials and challenges." *IEEE Communications Surveys & Tutorials* 19, no. 2 (2016): 721-742.

[13] Ding, Zhiguo, Xianfu Lei, George K. Karagiannidis, Robert Schober, Jinhong Yuan, and Vijay K. Bhargava. "A survey on non-orthogonal multiple access for 5G networks: Research challenges and future trends." *IEEE Journal on Selected Areas in Communications* 35, no. 10 (2017): 2181-2195.

[14] Dai, Linglong, Bichai Wang, Zhiguo Ding, Zhaocheng Wang, Sheng Chen, and Lajos Hanzo. "A survey of non-orthogonal multiple access for 5G." *IEEE communications surveys &Tutorials* 20, no. 3 (2018): 2294-2323.

[15] Tsai, Ming-Hsu, Jeng-Nan Lee, Hung-Da Tsai, Ming-Jhang Shie, Tai-Lin Hsu, and Hung-Shyong Chen. "Applying a Neural Network to Predict Surface Roughness and Machining Accuracy in the Milling of SUS304." *Electronics* 12, no. 4 (2023): 981.

[16] Anitha, D., and R. A. Karthika. "Hybrid Deep Learning-Based Adaptive Multiple Access Schemes Underwater Wireless Networks." *Intelligent Automation & Soft Computing* 35, no. 2 (2023).

[17] Shankar, Ravi, T. V. Ramana, Preeti Singh, Sandeep Gupta, and Haider Mehraj. "Examination of the non-orthogonal multiple access system using long short memory based deep neural network." *Journal of Mobile Multimedia* (2022): 451-474.

[18] Ahammed, Md Ferdous, A. Alim Molla, Rafiul Kadir, and Mohammad Ismat Kadir. "Deep bidirectional LSTM for the signal detection of universal filtered multicarrier systems." *Machine Learning with Applications* 10 (2022): 100425.

[19] Panda, Bibekananda, and Poonam Singh. "Signal Detection in NOMA Systems using DNN with Bidirectional LSTM." In *2022 2nd Odisha International Conference on Electrical Power Engineering, Communication and Computing Technology (ODICON)*, pp. 1-5. IEEE, 2022.

[20] Lin, Xin, Aijun Liu, Chen Han, Xiaohu Liang, Wenyu Wang, and Enyu Li. "Deep Learning-Based Nonstationary Channel Prediction in Tactical Vehicle-to-Vehicle Communication Environments." *Wireless Communications and Mobile Computing* 2022 (2022).

[21] Aldababsa, Mahmoud, Mesut Toka, Selahattin Gökçeli, Güneş Karabulut Kurt, and Oğuz Kucur. "A tutorial on nonorthogonal multiple access for 5G and beyond." *Wireless communications and mobile computing* 2018 (2018).

[22] Reddy, Bathula Siva Kumar, Kiran Mannem, and K. Jamal. "Software-defined radio-based non-orthogonal multiple access (NOMA) systems." *Wireless Personal Communications* 119, no. 2 (2021): 1251-1273.

[23] Ullah, Zaib, Fadi Al-Turjman, Uzair Moatasim, Leonardo Mostarda, and Roberto Gagliardi. "UAVs joint optimization problems and machine learning to improve the 5G and Beyond communication." *Computer Networks* 182 (2020): 107478.

[24] Omslandseter, Rebekka Olsson, Lei Jiao, Yuanwei Liu, and B. John Oommen. "User grouping and power allocation in NOMA systems: a reinforcement learning-based solution." In *Trends in Artificial Intelligence Theory and Applications. Artificial Intelligence Practices: 33rd International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, IEA/AIE 2020, Kitakyushu, Japan, September 22-25, 2020, Proceedings 33*, pp. 299-311. Springer International Publishing, 2020.

[25] Liaqat, M., Noordin, K. A., Abdul Latef, T., & Dimyati, K. (2020). Power-domain non-orthogonal multiple access (PD-NOMA) in cooperative networks: an overview. Wireless Networks, 26, 181-203.

[26] Lu, Feng, Mu Xu, Lin Cheng, Jing Wang, Junwen Zhang, and Gee-Kung Chang. "Non-orthogonal multiple access with successive interference cancellation in millimeter-wave radio-over-fiber systems." *Journal of Lightwave Technology* 34, no. 17 (2016): 4179-4186.

[27] Chege, Simon, and Tom Walingo. "Energy efficient resource allocation for uplink hybrid power domain sparse code nonorthogonal multiple access heterogeneous networks with statistical channel estimation." *Transactions on Emerging Telecommunications Technologies* 32, no. 1 (2021): e4185.

[28] Hameed, Zabit, and Begonya Garcia-Zapirain. "Sentiment classification using a single-layered BiLSTM model." *Ieee Access* 8 (2020): 73992-74001.

[29] Glorot, Xavier, and Yoshua Bengio. "Understanding the difficulty of training deep feedforward neural networks." In *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, pp. 249-256. JMLR Workshop and Conference Proceedings, 2010.

[30] Kingma, Diederik P., and Jimmy Ba. "Adam: A method for stochastic optimization." *arXiv preprint arXiv:1412.6980* (2014).

Mr. Neeraj Dwivediis pursuing Ph.D. from Amity University, Lucknow campus, an M. Tech from Dr. A.P.J. Abdul Kalam technical university, Lucknow, India in 2016, and completed a B. tech from Uttar Pradesh technical university, Lucknow, India in 2008.His research area is Non-Orthogonal Multiple Access based on the backscattering technique. His research interest includes applications of wireless sensor networks, machine learning, and artificial intelligence. He has published numerous research papers, book chapters, and articles in many reputed journals indexed in Scopus & SCI. He has presented several papers in Scopus-indexed reputed national as well as international conferences.

Sudeep Tanwar (Senior Member, IEEE) is working as a full professor at Nirma University, India. He is also a Visiting Professor with Jan Wyzykowski University, Poland, WSG University, Bydgoszcz, and the University of Pitesti, Romania. He received B.Tech in 2002 from Kurukshetra University, India, M.Tech (Honor's) in 2009 from Guru Gobind Singh Indraprastha University, Delhi, India, and Ph.D. in 2016 with specialization in Wireless Sensor Network. He has authored 05 books and edited 25 books, and more than 300 technical articles, including top-cited journals and conferences, such as IEEE TNSE, IEEE TVT, IEEE TII, IEEE TGCN, IEEE TCSC, IEEE IoTJ, IEEE NETWORKS, IEEE WCM, ICC, IWCMC, GLOBECOM, CITS, and INFOCOM. He initiated the research field of blockchain technology adoption in various verticals in the year 2017. His H-index as per Google Scholar and Scopus is 66 and 53, respectively. His research interests include blockchain technology, wireless sensor networks, fog computing, smart grid, and the IoT. He is a member of the Technical Committee on Tactile Internet of the IEEE Communication Society. Recently, He has been awarded a cash prize of Rs, 50,000 for publishing papers with 5+ Impact factors and publication of books with Springer, IET & CRC under the scheme of "Faculty Awards and Incentives" of Nirma University for the year 2019-2020. He has been awarded the Best Research Paper Awards from IEEE SCIoT 2022, IEEE IWCMC-2021, IEEE ICCCA-2021, IEEE GLOBECOM 2018, IEEE ICC 2019, and Springer ICRIC-2019. He has won Dr KW Wong's Annual Best Paper Prize (with 750 USD) for 2021 sponsored by Elsevier (publishers of JISA). He has served many international conferences as a member of the Organizing Committee, such as the Publication Chair for FTNCT-2020, ICCIC 2020, and WiMob2019, and a General Chair for IC4S 2019, 2020, 2021, 2022, ICCSDF 2020, FTNCT 2021. He is also serving the editorial boards of COMCOM-Elsevier, IJCS-Wiley, Cyber Security and Applications- Elsevier, Frontiers of Blockchain, SPY, Wiley, IJMIS Journal of Inder Science, JCCE, and JSSS. He is also leading the ST Research Laboratory, where group members are working on the latest cutting-edge technologies.

Dr. Sachin Kumar, a Ph.D. in Electronics from Dr R M L University, M.tech. and B.E in Electronics & Communication from Pune University, Presently with Amity University, Lucknow Campus. He has almost 20 years of academic and research experience. His research interest includes applications of Bio-Medical Signal Processing, Machine Learning, Artificial Intelligence & Applications of Wireless

Sensor Networks, He is an active member of many professional bodies IEEE, IETE, IAENG, ISC, and IET(UK), and he has published more than 80 Research papers, Book chapters, and articles in a number reputed Journals indexed in SCOPUS & SCI and Contributed 2 Books with international publishers. He is an active member of the Editorial Board/Reviewer in various reputed journals. Dr. Kumar has been instrumental in organizing many international conferences, has given invited talks, and chaired various technical sessions in national as well as international conferences of repute.

Sudhanshu Tyagi (SM'19) received a Ph.D. degree in Electronics & Communication Engineering from Mewar University, Chittorgarh, Rajasthan, India. He is currently an Assistant Professor with the Department of Electronics & Communication Engineering, Thapar Institute of Engineering and Technology, (Deemed to be University), Patiala, India. He has authored or co-authored more than 80 technical research papers in leading journals and conferences from IEEE, Elsevier, Springer, John Wiley, and others. Some of his research findings are published in top-cited journals such as IEEE-TII, IEEE-TVT, IEEE-WC, IEEE-SJ, FGCS, JNCA, PMC, CEE, IJCS, SPY, and TS. He has authored two books: Big Data Analytics (ISBN: 978-93-83992-25-8), and Mobile Computing (ISBN: 978-93-83992-25-6) in addition to this he has edited one book and published with Springer (online available) (ISBN: 978-93-83992-25-6). He was the recipient of the Best Research Paper award from Springer ICRIC 2019. He is a TPC member and reviewer of many international conferences across the globe. He is on the editorial board of Security & Privacy, Wiley. His current interests include routing issues in WSN, integration of sensors with the cloud, computational aspects of smart grids, and assessment of fog computing.