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Exploiting One-Dimensional Convolutional Neural Networks for Joint Channel Estimation and Signal Detection in Non-Orthogonal Multiple Access Systems

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Abstract:

Non-Orthogonal Multiple Access (NOMA) is a promising technology for the fifth and future generations of wireless communication networks, which increases spectral efficiency and reduces latency. However, NOMA performance can be affected by imperfect successive interference cancellation (SIC). Deep learning techniques have been proposed to aid in signal detection and channel estimation in NOMA systems. In this study, we propose a new approach using one-dimensional convolutional neural networks (1D CNN) to address the limitations of current deep learning methods. Unlike other deep learning methods that rely on time dependencies for data classification, 1D CNN uses a 1-dimensional convolution layer for feature extraction, resulting in high reliability. Simulation results demonstrate that our proposed method outperforms existing deep learning techniques in terms of sample error rate (SER) by 7dB. Moreover, reducing the cyclic prefix (CP) parameter increases inter-sample interference (ISI), but our method still achieves a 6 dB improvement over approaches in [11,13] and traditional channel estimation techniques like maximum likelihood (ML) at low signal-to-noise ratios (SNR).

Keywords: Deep neural networks, fifth generation, Hybrid NOMA-OFDM system, SIC, LSTM, BILSTM and 1D CNN.

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1. Introduction

The technology of (NOMA) is presented as an option for a future generation of wireless communication networks to achieve higher efficiency of spectrum. During the past few years, the need for mobile devices, with low latency, high connection, and high data transfer rates has been increasing significantly. Since NOMA provides service to multiple users simultaneously at the same frequency but with different power allocations, it satisfies these requirements. The efficiency is significantly increased by the frequency spectrum, connection speed, and transmission rate [1,2].

The fifth-generation (5G) wireless communication technology [3] thus has a lot of potential due to the NOMA approach. Send data from multi users is done using the superposition method at the transmitter end. To separate user information at the receiver, many complex algorithms were needed since NOMA serves numerous users simultaneously at the same frequency but with various power allocations. Incoming information is processed according to the channel condition between users and a base station or quality of service (QOS) requirements. Where the far user with low condition channel decodes first and considers other signals as noise then subtracts the result of decoding from the received signal at the near user, it has a high-condition channel and decodes the result of subtracting, this process is called successive interference cancelation (SIC) [4]. For SIC-based approaches, accurate channel state keep is required. Errors in signal identification and channel estimation are caused by imperfect (SIC) [5]. Many researchers use the concept of deep learning (DL) to identify NOMA signals at the receiver side to find solutions to the issue of imperfect SIC and its complexity [6]. DL is a branch of machine learning that uses artificial neural networks to learn from data.

Deep learning can also be applied in end-to-end learning settings, where the successful mapping of input-output data pairings requires little to no pre-processing or feature engineering [7]. In this situation of NOMA, DL algorithms can be trained to detect and decode signals by learning from a massive number of datasets of labelled NOMA signals. DL-based NOMA detection has been shown to outperform traditional detection methods, especially in cases where the SIC algorithm is imperfect or the channel conditions are hard to estimate precisely [8]. Recently there are many studies on the subject of DL aid NOMA signal detection and channel estimation to reduce SER where the power of DL was tested in several cases, including reducing influential parameters in the system, and the results were

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impressive[6,9]. Deep neural networks (DNN) were Suggested to aid signal detection and channel estimation at the receiver side in the uplink MIMO-NOMA system [10]. They suggested using a single DNN to decode the signal for each user at every SIC stride. Their approach reduced error propagation and system complexity where need fewer K-1 DNNs than DL-SIC. It can be seen from their research that if anything goes wrong with the decoding of the user signals, an error will occur on the receiver end because the decoding of the second user is based on the decoding of the first user, the third user depends on the first and second users and so on, they did not compare their findings to the traditional methods such as (ML, MMSE, and LS), which is more comparable to the ideal system and is used as a baseline in most studies. However, the results of their proposed approach outperform the other DL- SIC by about 2dB.

The authors suggested long short-term memory (LSTM) by modifying the number of hidden layers to 64 to detect uplink NOMA signals from two users [11]. Their proposed model was tested at different signal to noise ratio SNRs, and the results presented outperform the conventional methods (ML) even at low SNR by about 2dB and the others DL-LSTM by 4dB. Their approach reduced the overfitting of other LSTM systems.

The authors presented non-orthogonal multiple access (NOMA) depends on DL- LSTM to detect signals and make channel estimations from one operation [12]. They used the long short-term memory approach (LSTM) at a frequency-flat Rayleigh distributed fading channel. They utilized a 72-subcarrier OFDM framework with packet data. The total number of hidden layers used in DL-LSTM is 128. When the normal situation of the system their approach was better than LS but worse than that of MMSE in term SER. They reduced some of the parameters that affect the system, such as (P and CP) where their proposal proved superior to traditional methods such as (MMSE and LS) and so on, test their approach at different learning rates, their results were acceptable. They calculated the time required for training and found that there was no effect on time when increasing the number of paths. However, the results of their proposed approach outperform traditional methods such as (MMSE and LS) by about 1.9dB when reducing the number of pilots.

The authors suggested bidirectional long-term memory (BILSTM), where their approach learned the data from left to right and from right to left [13]. However, the results of their proposed model outperform traditional methods such as (ML) by about 0.8dB and other DL models (CNN) by 3dB.

The convolutional neural network (CNN)-based SIC scheme was suggested to enhance the efficiency of the single base station and several user NOMA systems [14]. On the other hand with current SIC methods, the suggested CNN-based SIC method can successfully reduce the error caused by a lack of SIC. Their proposed architecture consists of two convolutional layers, followed by a max pooling layer. A pair of dense layers with 256 and 128 neurons was then combined after two convolution and pooling layers. Every CNN layer's output is determined by its activation function, in this study they used sigmoid and exponential linear unit (ELU) as activation functions. However, the simulation results show that the CNN-based SIC method can effectively mitigate the problem of traditional SIC and achieve good detection accuracy.

The authors provided a hybrid CNN feature extractor and time-series LSTM layer to meet the NOMA-OFDM challenge [15]. They suggested dividing the data of the received signals using a CNN-based feature extraction, to meet inter-carrier and inter-symbol interference. The LSTM layers are suggested to solve the significant ISI caused by the multi-path channel effect, and the CNN-based feature extractor simulates the conventional process to deal with ICI caused by a Doppler shift. Their method operates in 5G situations at a doubly-selective tapped-delay line channel. It has been demonstrated that the proposed DL reduces the error rate when there are not enough pilots, and improves SER efficiency by about 4db in comparison using the conventional MMSE-SIC approach. They used an end-to-end framework, combining channel estimation and signal detection. In this work one dimension convolution neural network (1D-CNN) is suggested to detect two users uplink NOMA-OFDM signal and make channel estimation in one operation. Two convolution layers are used with (32, 64) filters and, three step size and two as a stride.

2. Proposed model and the mathematical theories

In this work the construction of a full deep learning system is the aim of this study. The proposed networks will use a two-user uplink NOMA structure with a single base station serving as a receiver to identify joined signals, similar to other works done in the region such as [11,12]. To distribute power, the transmitter and receiver have a fixed CSI. Since we want to compare our work with other comparable work when designing the uplink NOMA system, we must utilize the same principles and limits. The purpose of power distribution is to provide many users with an acceptable SINR for joint decoding at the receiving end. A single

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base station (BS) is connected to a group of multiple user systems in a typical microcell, as shown in Fig. 1. In this study, the two users are split into two groups: the near user, with a high condition channel with low power allocation factors, and the far user, that has a low condition channel and high power allocation factors [16]. The base station received the combined signals from two users plus channel noise. We used the hybrid NOMA-OFDM framework to send 64 subcarrier data packets and two pilots were used for channel estimation and hybrid signal detection [17]. As we already stated, the BS has highest CSI. The magnitude of data that was received can be calculated in terms of frequency response using the concept of **M** users with sub-carriers **R**, as shown in Eq. (1).

$$\gamma_R = \sum_{i=1}^{M} \sqrt{P_i(R)}\, H_i(R)\, \chi_i(R) + Z(R) \qquad (1)$$

Where: γ_R, $\chi_i(R)$ and $Z(R)$ the total receives signal, data transmitted from user (i) and channel addition noise with variance $\mathbf{Z(R)\sim Z(0,\sigma^2)}$ respectively. $P_i(R)$ Represent the user transmission allocated power for user (i) on subcarrier R.

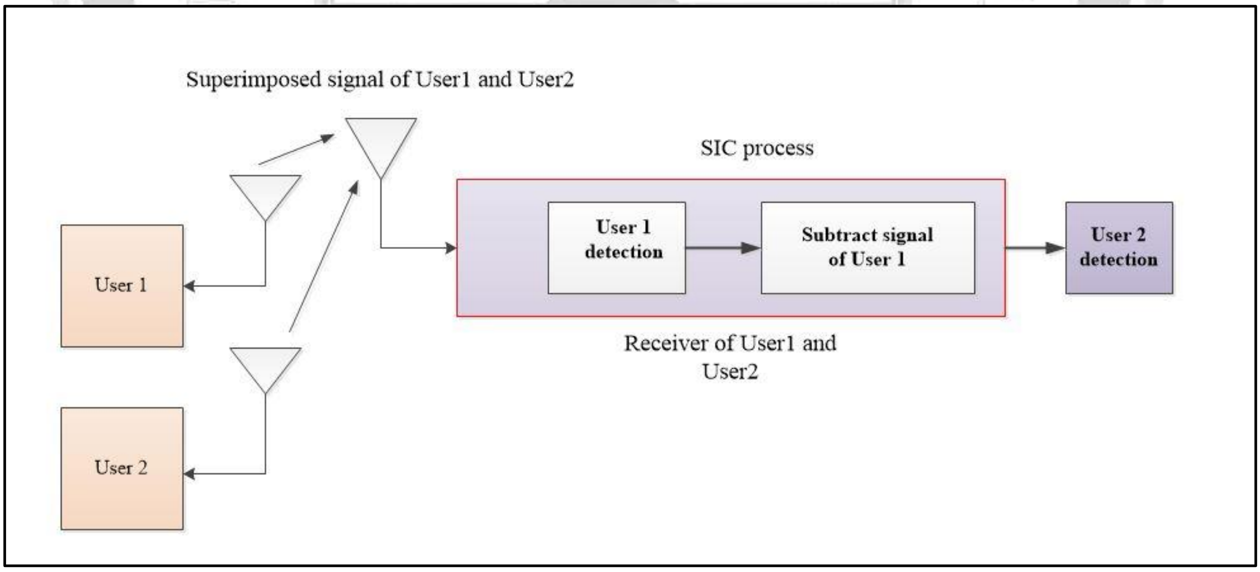

Fig .1 the NOMA uplink model with two users and one base station.

$H_i(R)$ Represent Deferential Fourier Transform (DFT) of a multipath channel's impulse rapid response $(\lambda_i(t))$ is showing in Eq. (2).

$$\lambda_i(t) = \sum_i^l \mu_{i,l}\,(t - \tau_{i,l}) \qquad (2)$$

Where: $\mu_{i,l}$,$\tau_{i,l}$: The complex channel gain and the corresponding time delay of the l th part for user (i) with numerous paths respectively.

When the combined signals from two users transmitted through the Rayleigh channel with 20 (l) multipath and cyclic prefix (CY) added at the time domain to prevent inter sample interference (ISI).

From the basic concept of NOMA, it depends on the allocated power coefficient to separate between users during transmission where the summation of the allocated power coefficient (ε_i) for user (i) is given in eq. (3) and eq. (4) respectively.

$$\sum_{i=1}^{M} \varepsilon_i\,(R) = 1 \qquad (3)$$

$$\varepsilon_i(R) = \frac{\mathrm{P}_i}{\sigma_i} \qquad (4)$$

Where: P_i power transmission factor for user i, σ_i noise variance. However from fig.1 the SIC approach at receiver end: user1 (near user) directly decoded signal with some interference form user2 we can be neglected, on the other hand the decoded signal of user1 subtract from the total received signal at user2 then decoded the result. As a result, the data rate or throughput of user 1 and user 2 is given by eq. (5) and eq. (6) respectively as follows [18]:

$$R_1 = \log_2\left(1 + \frac{P_{1|h_1|^2}}{P_{2|h_2|^2+\sigma_1{}^2}}\right) \qquad (5)$$

$$R_2 = \log_2\left(1 + \frac{P_{2|h_2|^2}}{\sigma_2{}^2}\right) \qquad (6)$$

From SIC methods we will conclude user2 depend on user1 and if error found when decode user1 the system loss its reliability then we needs to made channel estimation or channel equalization before SIC. In this work we depend on least- squares (LS), Minimum mean square error (MMSE) and maximum likelihood (ML) as traditional channel estimation methods with our proposed deep learning system. LS has less computational complexity compared to other channel estimation methods, but its main disadvantage is a high MSE rate. MMSE works more effectively than LS, but this method has more computational complexity, particularly because matrix inverted forms must be done whenever data modification [19]. ML has better performance than LS and MMSE but is more complicated than other methods because it needs a specific algorithm like Viterbi. Additionally, for ML to operate correctly, the channel must have every detail available.

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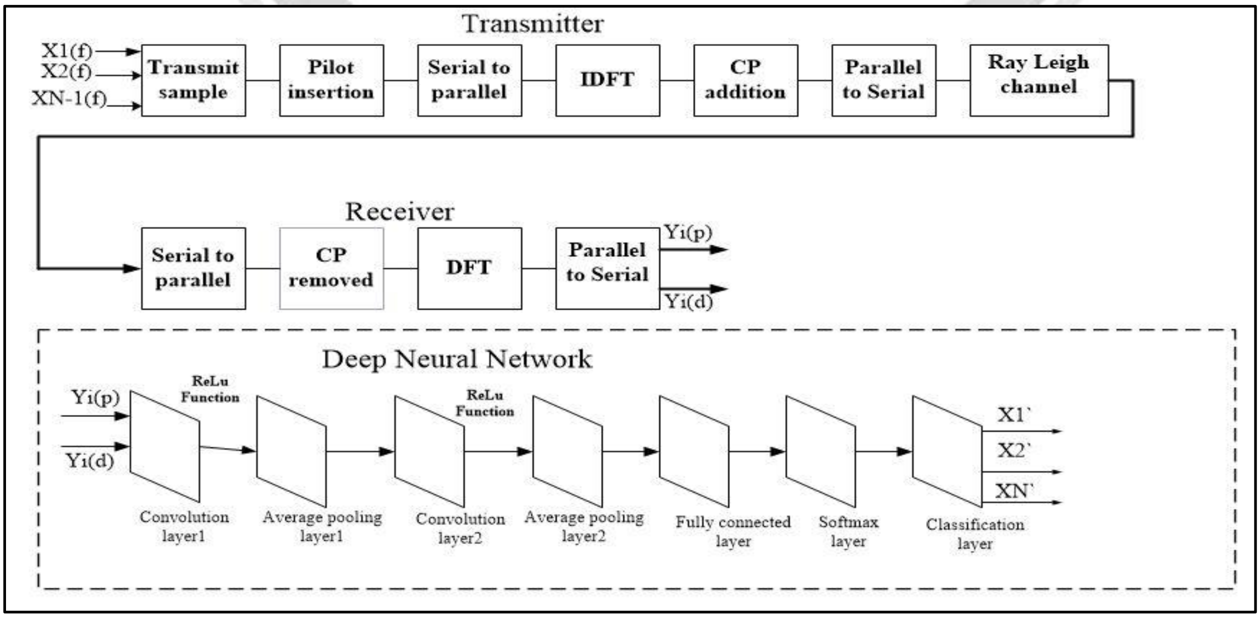
3. The proposed deep- learning system

In this part, we will present the structure of a proposed model where two users uplink the OFDM-NOMA system user1 has a high channel condition with a low power allocation coefficient transmitted signal X1, and user2 has a bad channel condition with a high power allocation coefficient transmitted signal X2 with the central base station to detect superposing signals. OFDM packets with 64 subcarriers and random phase shifts. A given packet has been divided into three parts: the first and second components are the pilot signal, and the third part is the data. The pilot is used to estimate channel characteristics and recover the signals. The quadrature phase shift keying (QPSK) modulation employs two bits per subcarrier for every symbol. If the two users are transmitted together, we will get one output of 16 possibilities. The OFDM packet was converted to the time domain and added a cyclic prefix (CP) to the facilitation process of mitigate from inter-sample interference (ISI). Feature vector shape (Yi) obtained from the incoming OFDM packet at the receiver and used to save it as sample data for the training collection. Each symbol in the OFDM packets has both real and imaginary values, which compose the feature set (Yi). The input size for training(x train) is $64 \times 3 \times 2 = 384$. Because the label is a number range of 1 to 16 and a total of 10000 packets of data are used then the number of labels and total data packets multiplied by each other produced a total data sample(y train) $10{,}000 \times 16 = 160{,}000$ to train the DL system. Figures (2.a, 2.b) show the proposed systems.



(a)

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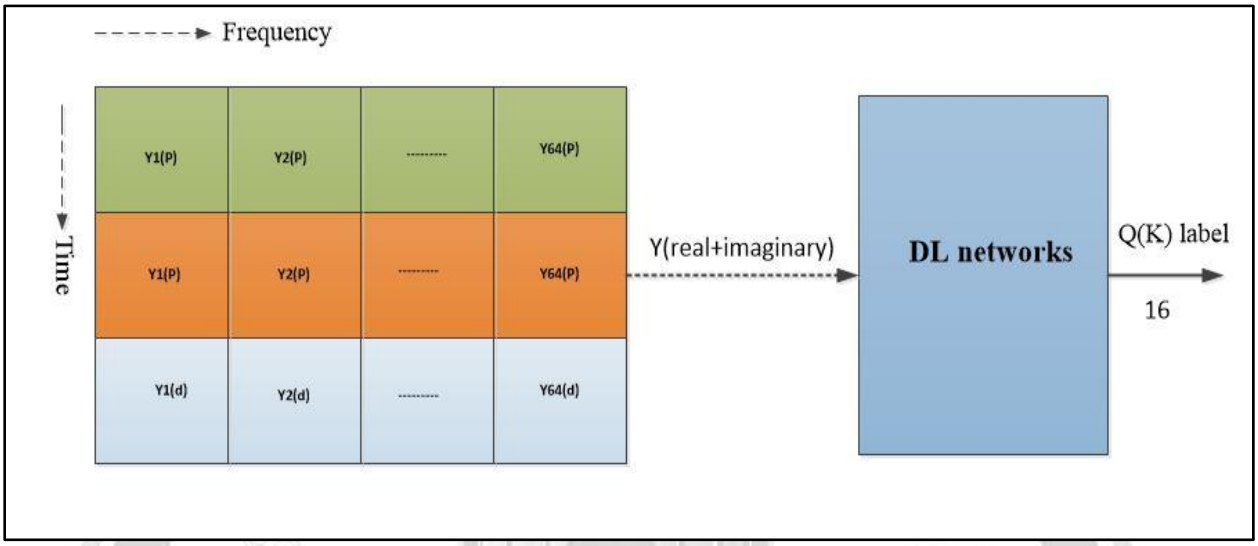

(b)

Fig. 2 (a) the proposed DL-aid NOMA-OFDM estimation approach, (b) OFDM packet

4. Proposed DL-1D CNN model

One-dimensional convolution neural networks (1D CNN) have gained popularity in various fields due to their high training speed and detection accuracy. Unlike other recurrent neural network types, 1D CNNs do not rely on time dependencies to classify data. 1D CNNs have previously been used in various applications, such as medical diagnosis and identifying cracks in metallic structures [20]. In this section, we propose a 1D CNN model to aid in signal detection for NOMA-OFDM systems. Our proposed model includes two sets of 1D convolution layers, followed by a Relu layer, global average pooling 1D layer, fully-connected layer, softmax layer, and classification layer. The first layer, the convolution layer, extracts features using the convolution process. In our proposed model, the first convolution layer consists of 32 filters with a step size of 3, while the second convolution layer has 64 filters with a step size of 3. The one-dimensional convolution layers transform input features into new forms called feature maps. The performance of the 1D CNN model can be improved by adjusting the filter size and number of filters for each set of convolution layers. The number of outputs of the feature map (O_F) can be calculated using eq. (7) [21].

$$O_F = \frac{X_p - F + 2P_a}{S} \qquad (7)$$

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Where: X_p number of input feature, F size of filter, P_a the amount of padding, S is stride (stride is the number of steps the kernel moves over the original input sequence).

The output of convolution layers inters to the rectified linear unit ReLU activation function. ReLU is a standard and powerful feature of deep learning networks. The output of the ReLU is a linear function, the principle of action of the ReLU is shown in the mathematical expression in equation below [22].

$$\text{ReLU}(x) = \max(0, x) = \begin{cases} x, & if \;\; x > 0 \; Active \\ 0, & if \;\; x < 0 \; Inactive \end{cases} \tag{8}$$

The f(x) of the ReLU will be zero for all x-values less than zero and the f(x) will be x for all x-values greater than zero. However, the ReLU lies between two convolution layers. The global average pooling layer is the second layer of 1D CNN, this layer is utilized to reduce the output of the convolutional layers into a single feature vector by taking the average for every feature map. Fully-connected layer process the output of the global average pooling layers and converted it to a vector of probabilities with a data size equal to the number of classes (16 label classes). The output of the fully connected layer is adjusted to the density function of probability over the output labels by the Softmax layer. The classification layer then produces a highly probable label class.

5. Simulated results and explanation

This part presents the simulated results from the proposed 1D CNN approach. Based on the simulation specifies shown in Table 1. The proposed 1D CNN scheme utilizes two users' NOMA-OFDM framework and produces signal detection according to SER against SNR. During the online testing process, the [4 to 24 every 2] dB SNR spectrum will be taken into consideration to simulate an accurate evaluation.

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Table1. The parameters of model.

parameter	value
Tool for modelling	Toolbox for deep learning in MATLAB
Form optimization	Adam
Subcarriers for OFDM	64
Number of pilot	64
Cyclic prefix (CY)	20,12
Number of multiple-path channel	20
Channel type	Rayleigh channel
USER NOMA	2
Packet number	10000
Batch size requirement	20000
Epochal duration	100
Rate of learning	1%
Filter size	3
Convolution layer1	32
Convolution layer2	64

5.1 Performance of proposed model in term SER

Referring to (figure 3) when a number of multipath 20 and cyclic prefix 20 and the pilot 64, our proposed model in yellow color is superior to all DL methods mentioned in the literature [11, 13] for user1 by about 6dB and for user2 by about 2dB until the SNR reaches to 21 dB the proposed model became identical to enhancement LSTM in reference 11. Also, our approach overcomes traditional methods such as ML even at low SNR.

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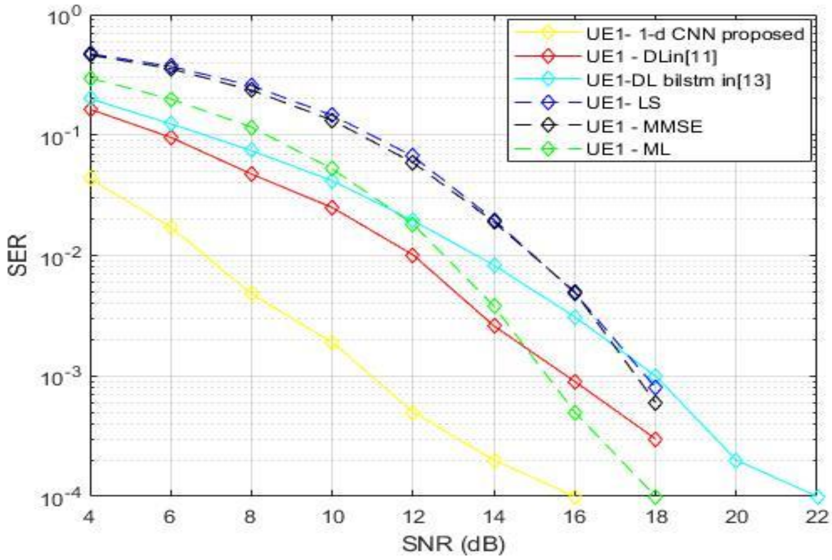
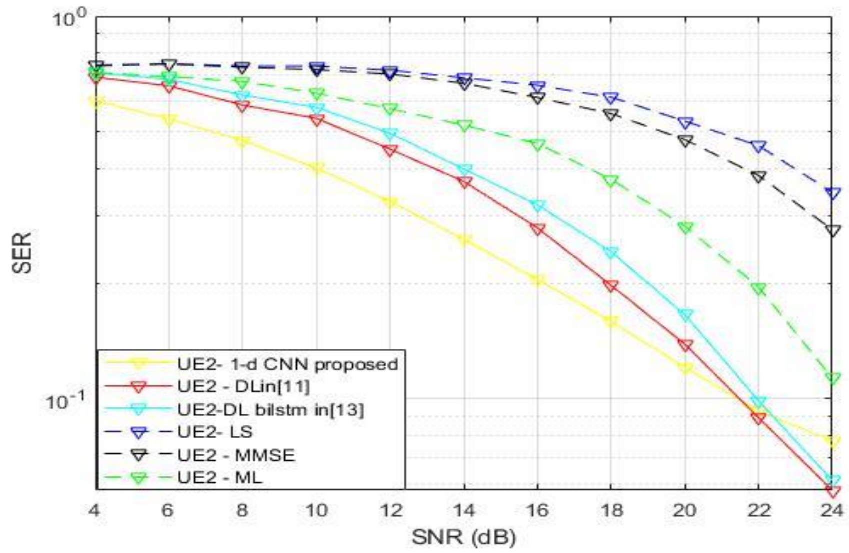


(a)



(b)

Figure.3 SNR / SER when the number of multipath is 20, CP is 20 and number of pilot is 64

(a) user 1, (b) user 2

5.2 Cyclic prefix changing

When making another test by reducing CP to 12 our proposed model for user1 outperforms the other DL approached [11, 13] by 6dB and traditional methods such as ML by 8 dB. While our proposed model for user2 outperforms the other DL systems [11,13] by about 3dB and

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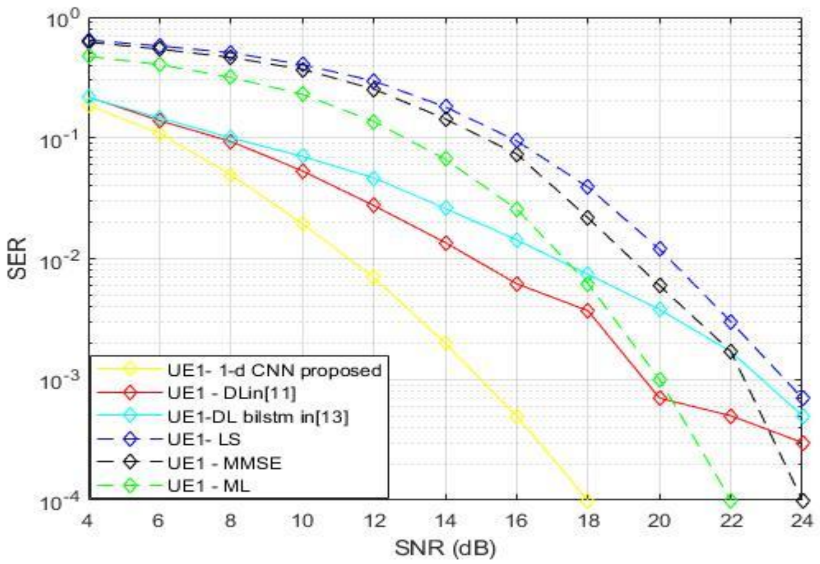
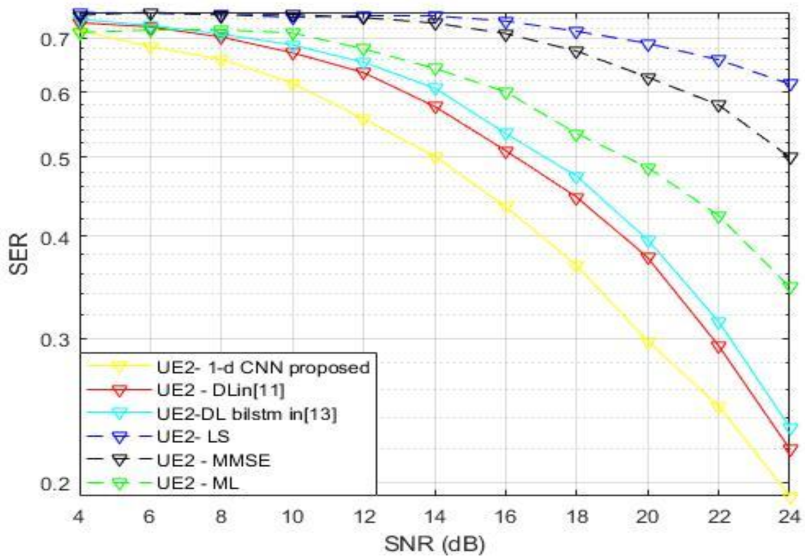
traditional methods such as ML by 8 dB.it is clear our suggested not affected by cyclic prefix reduction and increase ISI.Fig.4 show the impact of reducing the CP.



(a)



(b)

Figure.4 SNR / SER when the number of multipath is 20, CP is 12 and number of pilot is 64

(a) user 1, (b) user 2

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6. Conclusions

In conclusion, our proposed one-dimensional convolutional neural network (1D CNN) based deep learning system shows promising results in aiding hybrid NOMA-OFDM frameworks for joint signal detection and channel estimation. Our system uses two 1D convolutional layers for feature extraction, with a modification filter in the 1D CNN layer to enhance accuracy. One advantage of our approach is that it does not rely on time dependencies for data classification. Our proposed system outperforms other deep learning systems and conventional channel estimation methods, such as maximum likelihood (ML), by approximately 6dB. Moreover, our system maintains its performance even when reducing critical system parameters such as the cyclic prefix (CP). In contrast, other deep learning systems and traditional methods show reduced reliability and stability when these parameters are reduced. Overall, our approach shows great potential for improving the accuracy and reliability of NOMA systems, even in challenging conditions.

References

[1] Z. Ding and H. V. Poor, “Advantages of NOMA for Multi-User BackCom Networks,” *in IEEE Communications Letters*, vol. 25, no. 10, pp. 3408-3412, Oct. 2021.

[2] S. M. Islam, M. Zeng and O. A. Dobre, “NOMA in 5G systems: Exciting possibilities for enhancing spectral efficiency”*, arXiv preprint arXiv: 1706.08215*, vol.1, no.2, June. 2017.

[3] M. K. Hasan, M. Shahjalal, M. M. Islam, M. M. Alam, M. F. Ahmed and Y. M. Jang, “The Role of Deep Learning in NOMA for 5G and Beyond Communications,” in *2020 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), Fukuoka, Japan*, 2020.

[4] H. S. Ghazi and K. W. Wesołowski, “Improved Detection in Successive Interference Cancellation NOMA OFDM Receiver”, IEEE *Access*, vol. 7, pp. 103325-103335, Jul, 2019.

[5] M. R. Usman, A. Khan, M. A. Usman, Y. S. Jang and S. Y. Shin, “On the performance of perfect and imperfect SIC in downlink non orthogonal multiple access (NOMA),” in *2016 International Conference on Smart Green Technology in Electrical and Information Systems (ICSGTEIS), Denpasar, Indonesia*, 2016.

[6] V. Andiappan and V. Ponnusamy, “Deep learning enhanced NOMA system: A survey on future scope and challenges”, *Wireless Pers Commun 123*, pp. 1-39, Mar, 2022.

[7] H. Ye, L. Liang, G. Y. Li and B. -H. Juang, “Deep Learning-Based End-to-End Wireless Communication Systems With Conditional GANs as Unknown Channels”, in 2020 *IEEE Transactions on Wireless Communications*, vol. 19, no. 5, pp. 3133-3143, May, 2020.

[8] A. L. Ha, T. Van Chien, T. H. Nguyen, W. Choi and V. D. Nguyen, “Deep Learning-Aided 5G Channel Estimation,” in *2021 15th International Conference on Ubiquitous Information Management and Communication (IMCOM), Seoul, Korea (South)*, 2021.

[9] J. Thompson, "Deep Learning for Signal Detection in Non-Orthogonal Multiple Access Wireless Systems," in *2019 UK/ China Emerging Technologies (UCET), Glasgow, UK*, 2019.

[10] M. A. Aref and S. K. Jayaweera, "Deep Learning-aided Successive Interference Cancellation for MIMO-NOMA," *GLOBECOM 2020 - 2020 IEEE Global Communications Conference, Taipei, Taiwan*, 2020.

[11] A. H. Ali, R. S. A. Musawi, and K. A. Majdi, "Enhancements to the Deep Learning Signal Detection Model in Non-Orthogonal Multiple Access Receivers and Noisy Channels", *Journal of telecommunications and the Digital Economy*, Vol. 10, No. 1, pp. 92-100, Mar. 2022.

[12] A. Bhatt ,R. Shankar, G. Niedbala and A. Rupani, "Analysis of the Fifth Generation NOMA System using LSTM Algorithm" , *International Journal of Computing and Digital Systems*,vol.11,no.1, pp.215-223, Feb ,2022.

[13] D.V.Rahman, M. Habibur, M. A. S. Sejan, S. G. Yoo, M.A. Kim, Y.H. You, and H.K.Song, "Multi-User Joint Detection Using Bi-Directional Deep Neural Network Framework in NOMA-OFDM System", *Sensors*, Vol. 22, No. 18, pp.6994, Sep. 2022.

[14] S.Isaac, Y. G.Sun, D.Lee, S. H. Kim, J. Lee, J.H. Kim, Y.Shin and J.Y. Kim, "Deep learning based successive interference cancellation scheme in no orthogonal multiple access downlink network" ,Energies ,Vol.13, no. 23, pp. 6237, Nov, 2020.

[15] Y. Xie, K. C. Teh, and A. C. Kot, "Deep learning-based joint detection for OFDM-NOMA scheme" , *IEEE Communications Letters*, Vol. 25, No. 8, pp. 2609-2613, Aug, 2021.

[16] A. Emir, F. Kara, H. Kaya and H. Yanikomeroglu, "Deep Learning Empowered Semi-Blind Joint Detection in Cooperative NOMA", *IEEE Access*, vol. 9, pp. 61832-61852, 2021.

[17] Cho, Y. Soo, J.Kim, W. Y. Yang, and C. G. Kang, *MIMO-OFDM wireless communications with MATLAB, John Wiley & Sons*, 2010.

[18] M. Aldababsa, M. Toka, S. Gökçeli, G. K. Kurt, and O. Kucur, "A tutorial on non-orthogonal multiple access for 5G and beyond", *Wireless Communications and Mobile Computing*, Vol. 2018, Jun. 2018.

[19] B. Souleymane, S.R.Mondol and Z.Wei, "Comparative Performance Study of LS and MMSE Channel Estimation over Time Varying Channel in OFDM System", *International Journal of Engineering Research*, Vol.5, No.03, Mar, 2016.

[20] S. Kiranyaz, O. Avci, O.Abdeljaber, T. Ince, M.Gabbouj and D. J. Inman, "1D convolutional neural networks and applications: A survey", *Mechanical Systems and Signal Processing*, V.151, pp.107398, Apr, 2021.

[21] A.Krizhevsky, I.Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks", Communications of the ACM, vol. 60, no. 6, pp.84-90, May.2017.

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[22] J. Xu, Z. Li, B. Du, M. Zhang and J. Liu, “Reluplex made more practical: Leaky ReLU”, 2020 IEEE Symposium on Computers and Communications (ISCC), Rennes, France, pp. 1-7, 2020.

استغلال الشبكات العصبية التلافيفية أحادية البعد لتقدير القنوات المشتركة واكتشاف الإشارات في أنظمة الوصول المتعددة غير المتعامدة

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الخلاصة :

الوصول المتعدد غير المتعامد (NOMA) هو تقنية واعدة للجيل الخامس و الاجيال المستقبلية من شبكات الاتصالات اللاسلكية ، مما يزيد من كفاءة الطيف ويقلل من زمن الوصول. ومع ذلك، يمكن أن يتأثر أداء NOMA بإلغاء التداخل المتتالي غير المثالي (SIC). تم اقتراح تقنيات الذكاء الاصطناعي للمساعدة في الكشف عن الإشارات وتقدير القنوات في أنظمة NOMA. في هذه الدراسة ، نقترح نهجًا جديدًا باستخدام الشبكات العصبية التلافيفية أحادية البعد (1D CNN) لمعالجة قيود المحددة لأنظمة الذكاء الاصطناعي الحالية. على عكس طرق الذكاء الاصطناعي الأخرى التي تعتمد على تبعيات الوقت لتصنيف البيانات ، تستخدم 1D CNN طبقة التفاف أحادية البعد لاستخراج الميزات، مما يؤدي إلى موثوقية عالية. تظهر نتائج المحاكاة أن طريقتنا المقترحة تتفوق على تقنيات التعلم العميق الحالية من حيث معدل الخطأ في العينة (SER). علاوة على ذلك ، يؤدي تقليل معلمة البادئة الدورية (CP) إلى زيادة التداخل بين العينات (ISI) ، ولكن طريقتنا لا تزال تحقق تحسينًا بمقدار 6 ديسيبل على النهوج في (11،13) وتقنيات تقدير القنوات التقليدية مثل الاحتمال الأقصى (ML) عند إشارة منخفضة إلى– نسب الضوضاء (SNR).

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