Dynamic Resource Allocation and Energy Minimization in the NOMA System for Emerging Network using Deep Learning Algorithm

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ABSTRACT
The next generation of wireless network communication requires high data rates and low latency, posing significant challenges in resource allocation. In next-generation networks, resource allocation remains a major issue, with recent approaches focusing on both dynamic and static allocation strategies. The proposed approach utilizes deep learning models, particularly Long Short-Term Memory (LSTM) networks, to optimize power and spectrum allocation in real-time. By leveraging deep learning's ability to handle complex, high-dimensional data, the algorithm adapts to varying channel conditions and user requirements while minimizing energy consumption. A key feature of the proposed model is its capability to dynamically allocate resources based on Channel State Information (CSI) and Quality of Service (QoS) constraints, ensuring the efficient utilization of available bandwidth.

Keywords
Wireless Communication, NOMA, Power Allocation, Deep Learning

1. INTRODUCTION
Next-generation networks are playing vital role in modern life. The requirements of user needs and quality of services fulfil by employing non-orthogonal multiple access (NOMA)[1,2,3]. Employing NOMA scheme has improved spectral efficiency and performance of systems. the application of NOMA categorized into two groups such as power domain and code domain[4,5]. In NOMA systems, transmission power is allocated across the power domain depending on the distance between base stations (BSs) and users (Us), with some users receiving higher power and others lower power[6]. By enabling users with strong channel conditions to share subcarriers with users experiencing weaker channel conditions, NOMA enhances bandwidth utilization to its maximum potential[7,8]. Efficient power and spectrum allocation in the NOMA scheme enhances the system capacity of the communication model[9]. This efficiency relies on the optimal allocation of resources, achieved through swarm-based optimization algorithms and deep learning techniques. Deep learning algorithms play a significant role in the power domain, improving data transmission rates. They offer various optimization approaches, such as LSTM, CNN, and cascaded deep learning models[10,11]. In the downlink NOMA structure, the receiver device processes a multiplexed signal transmitted to multiple user terminals within the NOMA cell. Coordinated detection becomes crucial to mitigate interference generated by other user devices. In power-domain NOMA (PD-NOMA), multiuser detection is often managed using successive interference cancellation (SIC). During the SIC process, symbols from different users are decoded sequentially based on their Channel State Information (CSI) and the power allocation assigned to each user. To address the limitations of traditional methods, deep learning (DL) has made significant contributions to wireless communications, including applications in channel estimation (CE), signal detection (SD), constellation design, and modulation recognition. Additionally, DL techniques have been explored in 6G systems. For example, the authors in [12] proposed a novel codebook-based architecture for RIS-assisted communications, effectively overcoming challenges related to high implementation complexity and substantial pilot overhead. This paper proposes an efficient resource allocation strategy in the NOMA scheme for optimized power distribution. The proposed algorithm enhances the long-term memory capabilities of the Long Short-Term Memory (LSTM) model. The improvement is attributed to the mutual selection process between users and base stations. The rest of the article is organized as follows: Section II discusses the related work on the NOMA scheme, Section III presents the proposed methodology for the NOMA scheme, Section IV provides the experimental analysis, and Section V concludes the study.

2. RELATED WORK
Energy and spectrum are critical resources in emerging communication systems. The performance of these systems heavily relies on effective resource optimization. Recently, several researchers have employed deep learning and swarm intelligence-based algorithms for resource allocation within the NOMA modulation framework, enhancing the efficiency of resource management in emerging communication networks.In [1], an efficient neural network approach for user clustering in mmWave-NOMA is proposed, enabling offline neural network training for live clustering decisions in networks. However, it lacks flexibility in addressing SIC decoding capabilities for individual users and incurs high computational complexity in live decision-making. In [2], a low-complexity receiver design for joint activity and data detection is introduced, utilizing machine learning for low-complexity detection in GF-NOMA, with decision tree boundaries tailored to devices and modulation types. Generalization challenges involve power level management and channel dynamics. In [3], a DRL-based resource allocation scheme for D2D communications in cellular networks is presented. The scheme improves energy efficiency, fairness, and coordination among D2D users by analyzing outage probabilities of D2D and cellular links, though it does not handle overlapping D2D clusters or optimal solutions for complex multi-link detection. In [4], a DL-based channel estimation method for RIS-NOMA systems is

proposed, tackling channel estimation challenges in passive RIS-NOMA systems within 6G networks. However, estimation times may exceed channel coherence time. In [5], a simplified DQN structure for NOMA channel parameter prediction is introduced, combining RL algorithms with LSTM models. However, Q-learning complexity escalates in multi-user environments with large state spaces. In [6], the HyDNN framework for uplink NOMA-OFDM CE and SD systems is developed, combining a 1D-CNN feature extractor and BiLSTM layer for signal inference. The MMSE-SIC approach is suboptimal due to ICI and ISI issues, and performance varies with CP and pilot configurations. In [7], reinforcement learning algorithms for channel prediction and power allocation are explored, leveraging machine learning for power allocation and CSI estimation, though limitations are not specified. In [8], a novel interference coefficient estimation algorithm for NOMA VLC systems is introduced, featuring an optical NOMA communication system with a new SIC receiver. Challenges include error propagation, nonlinear distortion, and feedback complexity. In [9], DL-based SIC complexity for mMIMO-WNOMA systems with LS and MMSE estimators is analyzed. The study compares traditional FFT-based NOMA with a proposed Deep-mMIMO-WNOMA network, finding that imperfect CSI affects SIC and compromises data recovery. In [10], NOMA is presented as a key access method for future mobile generations, with ensemble methods' computational demands posing a barrier to real-time applications. In [11], neural networks for CE and IC in FBMC and OFDM systems are proposed, enhancing channel estimation accuracy and reducing computational complexity, though significant RNN training and data volume are required. In [12], channel capacity enhancement via frequency-domain signal vector derivation and particle filter equalization algorithms is investigated. Constraints include EH limitations and power restrictions. In [13], DNNs are utilized to enhance NOMA performance in uplink communications, improving synergy among NOMA, MUD, and DNNs. Traditional MUD methods may not fully exploit NOMA's benefits, especially in beamforming vector allocation. In [14], a MA-DRL-based SGF-NOMA algorithm is proposed, addressing SIC imperfections and distributed power control but facing challenges with RL training complexity and overestimation issues in DQN. In [15], the OBAUS scheme for secrecy performance in cooperative NOMA is introduced, exploring DNN-based optimization for real-time prediction and impact of network parameters. In [16], a two-step DQN training model addresses the PA problem in multi-user communication. Despite outperforming model-driven algorithms, interference and performance instability remain challenges with large-scale fading effects. In [17], a multi-user communication model with Q-learning-based user pairing and power allocation in CRN-NOMA is proposed, though complexity arises from multiple constraints in downlink optimization. In [18], MAB and DDQN algorithms for UAV energy-efficient communications tackle path design and power distribution, though the computational burden of exhaustive NOMA pairing and lack of energy-efficient focus are noted. In [19], a cooperative THz mMIMO-NOMA base station optimization method is proposed, using a multi-layer antenna and fuzzy c-means clustering for user grouping. However, dynamic environment adaptation and power constraints pose challenges. In [20], an ACO-based edge learning scheme in NOMA networks is proposed, optimizing learning error and power allocation, with wireless channels impeding ultra-fast edge learning. In [21], a metaheuristic approach to optimize power allocation is presented, but OMA's adaptability and resource flexibility remain limited. In [22], an AoI minimization approach for WPCRN with power optimization is developed, addressing practical constraints like spectrum sensing and SIC imperfection. In [23], a hybrid NOMA-TDMA system for sum-throughput maximization in WPINs is presented, with energy limitations posing a challenge for IoT battery life. In [24], a user association algorithm for NOMA-enabled vehicular HetNet optimizes bandwidth allocation, though interference limits spectrum utilization. In [25], a hierarchical game for multi-carrier system efficiency uses a clustering algorithm for power allocation in hybrid NOMA, facing challenges with co-channel interference and computational complexity in mMTC networks.

3. PROPOSED METHODOLOGY

The CDNN is implemented at the Base Station (BS), where, following training, it allocates varying power levels to individual users. Although the CDNN framework does not directly model physical users, it leverages extracted features from channel links and users as training examples. This approach ensures that information regarding all users and channel conditions is encompassed within the training data. To further enhance system performance, we introduce effective learning methodologies tailored to train the CDNN. Moreover, building upon the deep learning-based framework, we propose advanced algorithms aimed at optimizing both sum data rate and energy efficiency within the MIMO-NOMA system. These algorithms represent a significant advancement in leveraging deep learning techniques for enhancing the performance of wireless communication systems.

Algorithm 1 CDNN based training algorithm for MIMO-NOMA.

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Algorithm 1 CDNN based training algorithm for MIMO-NOMA.

Input: Environment simulator, channel vectors hm, and precoding matrix P.Output: CDNN.

1:Start running environment simulator to generate the wireless channel, which is corrupted by AWGN and other distortion.

2: Generate a set of training samples. These samples comprise channel vectors hm and precoding matrix P .

3: Develop the proposed CDNN framework. Then, initialize the learning rate, and the loss rate. The weights of the network are initialized by the well-known Xavier method. Furthermore, we set the batch size. Additionally, we set the error threshold as $\sigma = 10-7$.

4: Initialize parameters: $P = 0$ and $\beta m \in \{0, 1\}, \forall i, j$.

5: while error $\geq \sigma$: Train the CDNN based on the given

training samples to approximate problem (11) according to the proposed learning mechanism by the SGD.

6: Update the network parameters of the CDNN

7: Update the weight w and the output of each layer of the CDNN.

8: end while

9: return: CDNN.

Algorithm 2 CDNN based testing algorithm for MIMO-NOMA.

input: Environment simulator, CDNN.

Output: Precoding matrix P, power allocation coefficients βm.

1: Load the well-trained CDNN framework.

2: Start running environment simulator to generate wireless channel, and add specific distortion or noise to the channel.

3: Process the CDNN.

4: Update the output of each layer of the CDNN.

5: Compute the precoder pm in the m-th cluster, as well as

power allocation coefficients βm ∈ [0, 1].

6: Obtain P¯ based on the precoder p¯m, ∀m.

7: Calculate power allocation factor according to $\beta m = \frac{|P_m|}{P}$ and then use similar way to compute βm,k.

8: end while

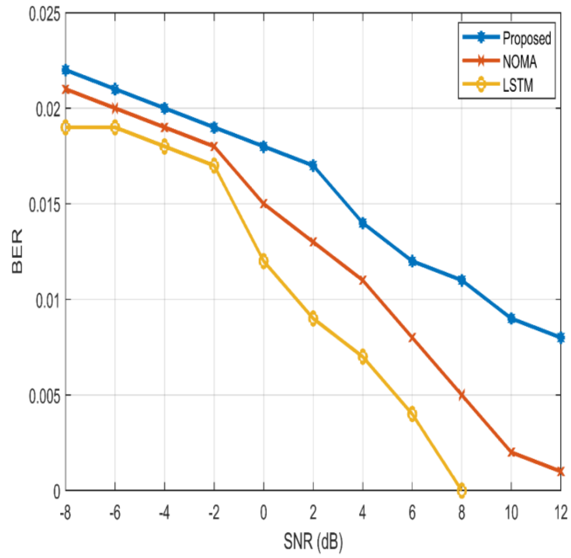
9: return: Precoding matrix P and power allocation coefficients βm, k.

4. EXPERIMENTAL ANALYSIS

To validate the proposed deep learning algorithm for resource optimization in the NOMA scheme, MATLAB tools (version 2018R(a)) were used. The performance of the model was analysed using parameters such as BER, outage probability, data rates, and sum rates. The proposed algorithm was evaluated with two groups of users, designated as User-1 and User-2. The employed deep learning algorithm is Long Short-Term Memory (LSTM).

Table 1 Simulation Parameters of NOMA scheme for allocation of Resources[20,21,22]

Parameters	Value
Carrier frequency	2 GHz
Base station (BS) power	46 dBm
System bandwidth (BW)	5–10 MHz
Number of users per cell (N)	10–20
Bandwidth per user	5.4 MHz
Number of data subcarriers	1200
Number of pilot subcarriers (xi)	4
Number of guard-band subcarriers	76
Channel matrices (Hi)	Rayleigh or Rician fading
AWGN (w)	−10 to 30 dBm
Power allocation coefficients (p)	2/3 and 1/3 3/4 and ¼ 4/5 and 1/5



We observe that the value of the proposed is better than the other two methods. The value of the proposed, which is better, is 0. 022 at SNR (dB) -8, and the value of NOMA, which is better, is 0. 021 at SNR (dB) -8. We saw that the value of LSTM, which is better than the other two methods, is as follows: which is 0,019 at SNR (dB) -8.

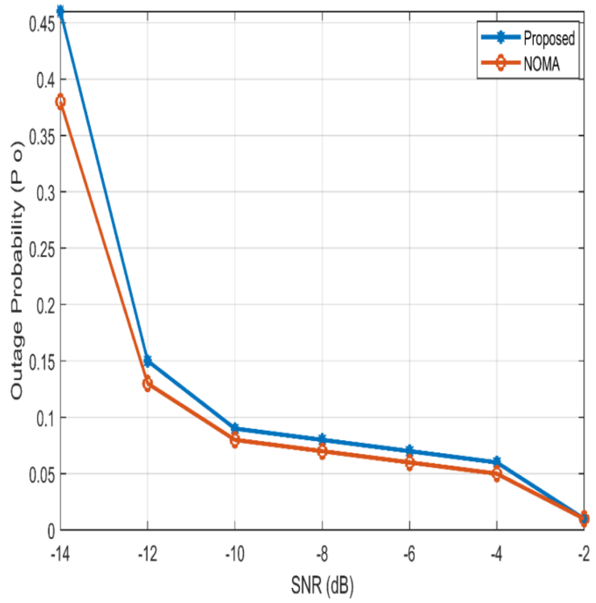


Figure: 3 Comparative analysis of outage probability (P o) and SNR (dB).

We observe that the value of the proposed is better than the value of NOMA, which is as follows: The value of the proposed is better, which is 0. 46 at SNR (dB) -14, and the value of NOMA, which is 0. 38 at SNR (dB) -14. Which is less than proposed.

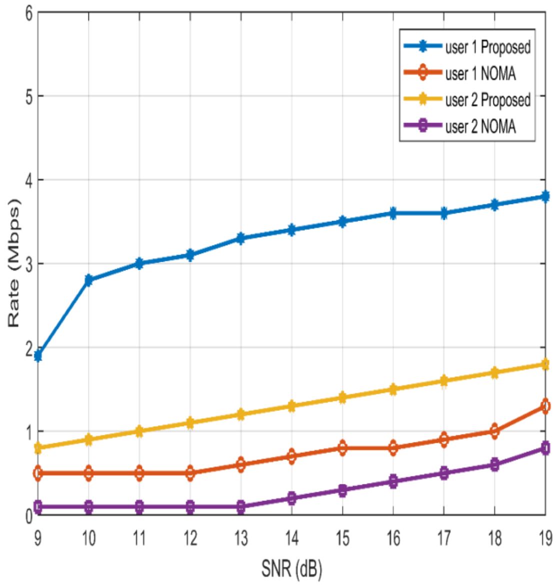
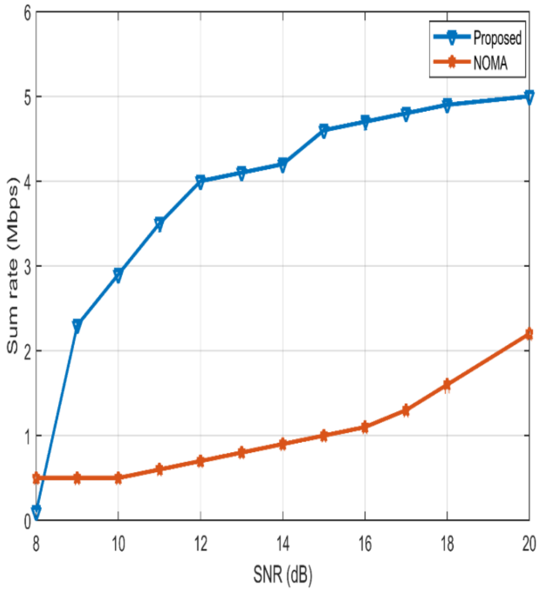


Figure: 4 Comparative analysis of using user-1-proposed, user-1-NOMA, and user-2 proposed, user-2-NOMA, of techniques with rate (Mbps) and SNR (dB).

We observe that the value of user 1 proposed and user 2 proposed is better than user 1 NOMA and user 2 NOMA method. The value of user 1 proposed is 3.8 at SNR (dB) 19 and the value of user 2 proposed is 3.8 at SNR (dB) 19. Same User 1 NOMA value SNR (dB) is 1.3 at 19 and User 2 NOMA value SNR (dB) is 0.8 at 19 which is less.



We observe that the value of the proposed is better than the value of NOMA, which is as follows: The value of the proposed is better, which is 5 at SNR (dB) 20, and the value of NOMA, which is 2.2 at SNR (dB) 20, which is less than proposed.

5. CONCLUSION & FUTURE WORK

This paper introduces a novel deep learning-based algorithm designed for optimizing resource allocation in the NOMA scheme. The proposed approach focuses on improving efficiency in terms of energy utilization and reducing outage probability, which are critical performance metrics in modern wireless communication systems. The algorithm employs a mutual cascading Deep Neural Network (CDNN) framework, which integrates multiple deep learning models in a sequential manner to enhance feature extraction and decision-making processes. By leveraging this cascading architecture, the algorithm achieves a robust balance between computational complexity and accuracy, making it well-suited for dynamic and resource-intensive environments such as NOMA. Compared to existing algorithms, including Long Short-Term Memory (LSTM) networks and other deep learning models, the proposed CDNN-based approach demonstrates superior efficiency and performance. The mutual cascading framework not only enhances the adaptability of the model to varying user and channel conditions but also ensures better optimization of power and bandwidth allocation. Experimental results highlight the significant advantages of the proposed algorithm, including lower energy consumption, reduced outage probability, and improved overall system performance. These findings underline the potential of CDNN as a transformative approach for resource allocation in NOMA systems.

6. REFERENCES

[1] Rajasekaran, Aditya S., and Halim Yanikomeroglu. "Neural network aided user clustering in mmWave-NOMA systems with user decoding capability constraints." IEEE Access 11 (2023): 45672-45687.

[2] Shahab, Muhammad Basit, Sarah J. Johnson, and Stephan Chalup. "Data-Driven Low-Complexity Detection in Grant-Free NOMA for IoT." IEEE Internet of Things Journal (2023).

[3] Jeong, Yun Jae, Seoyoung Yu, and Jeong Woo Lee. "DRL-Based Resource Allocation for NOMA-Enabled D2D Communications Underlay Cellular Networks." IEEE Access (2023).

[4] Nguyen, Chi, Tiep M. Hoang, and Adnan A. Cheema. "Channel estimation using CNN-LSTM in RIS-NOMA assisted 6G network." IEEE Transactions on Machine Learning in Communications and Networking 1 (2023): 43-60.

[5] Gaballa, Mohamed, and Maysam Abbod. "Simplified Deep Reinforcement Learning Approach for Channel Prediction in Power Domain NOMA System." Sensors 23, no. 21 (2023): 9010.

[6] Rahman, Md Habibur, Mohammad Abrar Shakil Sejan, Md Abdul Aziz, Young-Hwan You, and Hyoung-Kyu Song. "HyDNN: A hybrid deep learning framework based multiuser uplink channel estimation and signal detection for NOMA-OFDM system." IEEE Access (2023).

[7] Gaballa, Mohamed, Maysam Abbod, and Ammar Aldallal. "A Study on the Impact of Integrating Reinforcement Learning for Channel Prediction and Power Allocation Scheme in MISO-NOMA System." Sensors 23, no. 3 (2023): 1383.

[8] Mohsan, Syed Agha Hassnain, Yanlong Li, Zejun Zhang, Amjad Ali, and Jing Xu. "Uplink and Downlink NOMA Based on a Novel Interference Coefficient Estimation Strategy for Next-Generation Optical Wireless

Networks." In Photonics, vol. 10, no. 5, p. 569. MDPI, 2023.

[9] Ahmad, Muneeb, and Soo Young Shin. "Deep Learning aided SIC for Wavelet-based massive MIMO-NOMA." Authorea Preprints (2023).

[10] Smirani, Lassaad K., Leila Jamel, and Latifah Almuqren. "Improving Channel Estimation in a NOMA Modulation Environment Based on Ensemble Learning."

[11] Godavari, swapnasunkara, chintanagaraju, kondamanoj kumar, dryeligetiraju, karthik kumar vaigandla, and r. A. D. H. A. K. R. I. S. H. N. A. Karne10. "Analysis of papr, ber and channel estimation in multi carrier modulation systems using neural networks." Journal of Theoretical and Applied Information Technology 102, no. 5 (2024).

[12] KUMAR, Manoj, Manish KUMAR PATIDAR, and Narendra SINGH. "Channel Capacity Enhancement with Nonlinear Distorted Signal Detection Using OFDM-NOMA Systems with Optimization System." Economic Computation and Economic Cybernetics Studies and Research 58, no. 2 (2024).

[13] Khambra, Anoop Kumar, and Rajesh Kumar Rai. "Enhancing Uplink Communication with Multi-User Detection in NOMA Through Deep Neural Networks." International Journal of Innovative Research in Technology and Science 12, no. 2 (2024): 464-469.

[14] Semi-Grant-Free, N. O. M. A. "Toward Autonomous Power Control in Semi-Grant-Free NOMA Systems: A Power Pool-Based Approach."

[15] Pramitarini, Yushintia, Ridho Hendra Yoga Perdana, Kyusung Shim, and Beongku An. "Opportunistic Scheduling Scheme to Improve Physical-Layer Security in Cooperative NOMA System: Performance Analysis and Deep Learning Design." IEEE Access (2024).

[16] Soltani, Sepehr, Ehsan Ghafourian, Reza Salehi, Diego Martín, and Milad Vahidi. "A Deep Reinforcement Learning-Based Technique for Optimal Power Allocation in Multiple Access Communications." Intelligent Automation & Soft Computing 39, no. 1 (2024).

[17] He, Xiaoli, Yu Song, and Hongwei Li. "Research on User Pairing and Power Allocation in Multiuser CRN-NOMA Networks Based on Reinforcement Learning." Journal of Sensors 2024, no. 1 (2024): 6642221.

[18] Gendia, Ahmad, Osamu Muta, Sherief Hashima, and Kohei Hatano. "Energy-Efficient Trajectory Planning with Joint Device Selection and Power Splitting for mmWaves-Enabled UAV-NOMA Networks." IEEE Transactions on Machine Learning in Communications and Networking (2024).

[19] Shahjalal, Md, Md Habibur Rahman, Md Morshed Alam, Mostafa Zaman Chowdhury, and Yeong Min Jang. "DRL-Assisted Dynamic Subconnected Hybrid Precoding for Multi-Layer THz mMIMO-NOMA System." IEEE Transactions on Vehicular Technology (2024).

[20] Garcia, Carla E., Mario R. Camana, and Insoo Koo. "ACO-based Scheme in Edge Learning NOMA Networks for Task-Oriented Communications." IEEE Access (2024).

[21] Dipinkrishnan, R., and Vinoth Babu Kumaravelu. "Enhancing Sum Spectral Efficiency and Fairness in NOMA Systems: A Comparative Study of Metaheuristic Algorithms for Power Allocation." IEEE Access 12 (2024): 85165-85177.

[22] He, Tao, Yingsheng Peng, Yong Liu, and Hui Song. "AoI-oriented Resource Allocation for NOMA-based Wireless Powered Cognitive Radio Networks based on Multi-agent Deep Reinforcement Learning." IEEE Access (2024).

[23] Afridi, Abid, Iqra Hameed, Carla E. García, and Insoo Koo. "Throughput Maximization of Wireless Powered IoT Network with Hybrid NOMA-TDMA Scheme: A Genetic Algorithm Approach." IEEE Access (2024).

[24] Nauman, Ali, Mashael Maashi, Hend K. Alkahtani, Fahd N. Al-Wesabi, Nojood O. Aljehane, Mohammed Assiri, Sara Saadeldeen Ibrahim, and Wali Ullah Khan. "Efficient resource allocation and user association in NOMA-enabled vehicular-aided HetNets with high altitude platforms." Computer Communications 216 (2024): 374-386.

[25] Benamor, Amani, Oussama Habachi, Inès Kammoun, and Jean-Pierre Cances. "Multi-armed bandit approach for mean field game-based resource allocation in NOMA networks." EURASIP Journal on Wireless Communications and Networking 2024, no. 1 (2024): 42.