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Machine Learning Technique for Resource Allocation Optimization in NOMA Systems

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***Abstract*— Non-Orthogonal Multiple Access (NOMA) has emerged as a key technology in modern wireless communication systems, enabling improved spectral efficiency and user connectivity. However, efficient resource allocation in NOMA systems remains a significant challenge due to interference management, power allocation constraints, and user fairness. Traditional optimization methods often struggle with the complexity and dynamic nature of wireless networks. Machine Learning (ML) techniques offer promising solutions by leveraging data-driven approaches to optimize power allocation, user clustering, and scheduling decisions in real-time. This paper explores the application of ML algorithms, including Reinforcement Learning (RL), Deep Neural Networks (DNNs), and metaheuristic techniques, for resource allocation in NOMA systems.**

Keywords—NOMA, Machine Learning, IOT, Resource allocation, Cluster.

I. INTRODUCTION

With the rapid evolution of wireless communication technologies, the demand for high data rates, massive connectivity, and efficient spectrum utilization has increased significantly. To address these challenges, Non-Orthogonal Multiple Access (NOMA) has been proposed as a key multiple access technique in 5G and beyond (6G) networks. Unlike conventional Orthogonal Multiple Access (OMA) schemes, where users are assigned distinct time, frequency, or code resources, NOMA allows multiple users to share the same frequency and time resources by utilizing power-domain multiplexing and Successive Interference Cancellation (SIC) techniques. This approach enhances spectral efficiency, improves system capacity, and ensures seamless connectivity in dense wireless environments.

One of the fundamental challenges in NOMA systems is optimal resource allocation, which includes power distribution, user pairing, and channel assignment. Traditional resource allocation techniques, such as convex optimization, game theory, and heuristic algorithms, have been extensively explored. However, these methods often struggle to handle the growing complexity and dynamic nature of modern wireless networks. As a result, there is an increasing interest in applying Machine Learning (ML) techniques to optimize resource allocation in NOMA systems.

ML-driven approaches offer significant advantages by leveraging data-driven models that can learn and adapt to network variations in real time. Various ML techniques have been explored for resource allocation in NOMA, including:

- **Supervised Learning**: Techniques such as Deep Neural Networks (DNNs) are used to predict optimal power allocation and user clustering based on historical network data.
- **Reinforcement Learning (RL)**: RL algorithms, such as Deep Q-Networks (DQN) and Multi-Agent Reinforcement Learning (MARL), enable dynamic resource allocation by interacting with the network environment and making intelligent decisions based on rewards.
- **Unsupervised Learning**: Clustering algorithms like k-means and self-organizing maps are used for user pairing and subchannel allocation.
- **Metaheuristic Optimization**: Techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) are integrated with ML to enhance search efficiency in complex resource allocation problems.

These ML techniques aim to optimize key performance metrics such as spectral efficiency, energy efficiency, fairness, latency reduction, and interference management. For instance, RL-based approaches can dynamically adjust power levels and user scheduling in real-time, outperforming traditional optimization methods in highly dynamic network environments. Moreover, the integration of Deep Learning (DL) with Reinforcement Learning (DRL) has further enhanced the ability to make intelligent resource allocation decisions with reduced computational complexity.

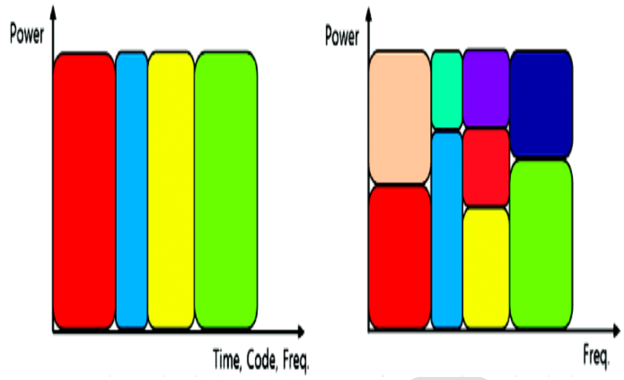

Figure 1: (a) Orthogonal multiple access (b) non-orthogonal multiple access

Despite its potential, the application of ML for NOMA resource allocation presents several challenges. The high computational complexity of deep learning models, the need for large-scale training data, and the difficulty in ensuring real-time adaptability are critical concerns. Additionally, ML models require efficient generalization techniques to perform well under diverse network conditions, including varying user mobility, channel fading, and traffic patterns. Furthermore, ensuring the security and privacy of ML-driven resource allocation mechanisms is another important aspect that needs attention, especially in decentralized NOMA architectures.

II. LITERATURE SURVEY

S. Rezwan et al., [1] In order to cater to the diverse demands of its customers, fifth-generation (5G) new radio (NR) services were created. These services include massive machine type communication (mMTC), enhanced mobile broadband (eMBB), and ultra-reliable and low-latency communication (URLLC). In order to meet these quality-of-service needs, the SIC method and the power domain were used to create non-orthogonal multiple access (NOMA), which enables several devices to share a single frequency.

By using the MIMO-NOMA VEC, an allocation technique was devised by H. Zhu et al. [2] to optimise long-term reward, while factoring in the unpredictable arrival of tasks and channel variation. This research constructs a decentralised DRL framework that uses local observations to characterise the power allocation optimisation issue, in contrast to previous work that has depended on a centralised kind of deep reinforcement learning (DRL). The distributed DRL architecture makes use of the DDPG approach to determine the optimal power distribution model. According to the findings of the simulations, our proposed strategy for distributing electricity is better than the existing ones.

A research conducted by M. Katwe found [3] Here, we take on the difficult task of finding the sweet spot for energy efficiency in a UAV-based full-duplex non-orthogonal multiple-access (FD-NOMA) network. To start, we provide an original and simplified adaptive-geometric distribution (AGD) that may equally allocate resources among all users while keeping cluster sizes equal, thereby minimising user interference in the system under study. Then, taking into account the location of the UAV and the requirements of its downlink (DL) and uplink (UL) users, we present an optimisation problem that aims to maximise energy efficiency within the constraints of a transmit power budget.

X. Liu [4] propose that IIoT use the ground-based cellular network to augment satellite coverage in areas that are blacked out. Integration of IIoT devices into power allocation and network selection processes may help bring down transmission costs. Results from the simulation show that NOMA is better than other methods in the satellite IIoT, and that it improves transmission performance for QoS-guaranteed resource allocation.

W. Yin [5] research suggests that in order to boost radio throughput, new radio access techniques are required. One intriguing potential technique for 6G wireless networks is nonorthogonal multiple access (NOMA), which takes use of multiuser diversity in the power domain. Research in this area focusses on heterogeneous multicarrier NOMA networks that use downlink joint device assignment and power allocation. The optimal solution to the problem of optimising network throughput involves combining the limits of total power at each base station with the minimum transmission rates for devices and the maximum numbers of accessible devices for each subchannel.

Xu et al., [6] may decrease energy use for all users by considering offloading choices, local CPU frequency scheduling, power control, compute resource, and subchannel resource allocation. Due to the close relationship between the offloading choice and resource allocation, solving the optimisation problem is challenging. By iteratively addressing the two sub-problems of offloading choice and resource allocation, we provide a successful approach to finding the combined solution.

J. Cheng et al., [7] cooperative relaying downlink transmission employing D2D-assisted non-orthogonal multiple access (DC-NOMA) is detailed. Our goal is to enhance two performance metrics: the overall ergodic sum rate (ESR) and the block error rate (BER) at the output of the detection receiver. First, we check whether the optimisation problem of ESR maximisation is convex; second, we prove that it is not strictly concave. In contrast to earlier research that only optimised the power coefficient in one step, we provide a coordinated two-stage iterative search-based power allocation technique to maximise the ESR.

An article by Y. Zhuang [8] This article presents research on cognitive radio networks (CRNs) that employ power-domain non-orthogonal multiple-access (P-DOMA) as an RF underlay. Using the acquired energy, the HTT mode enables secondary transmitters (STs) to broadcast data based on power-domain NOMA simultaneously. In this mode, the primary users' stringent interference threshold and the collected energy both have a significant impact on the secondary system's throughput. Ambient backscatter communication (ABC) is another promising new approach that enables STs to transmit data by modifying and reflecting RF frequencies that occur naturally.

According to S. Bayat et al., [9] a heterogeneous network that enables simultaneous wireless information and power transmission (SWIPT) is called HetNet, and it is built on separated architecture (SA). In this paper, we focus on the design of a multi-channel MISO-NOMA method for use in HetNets, where each base station (BS) serves many ID and EH users using a non-linear energy harvesting model and various antennas. Together, an energy beamforming design, subcarrier assignment, and beamforming may achieve the maximum throughput in this configuration.

B. K. S. Lima et al., [10] investigated cooperative networks that use non-orthogonal multiple access (NOMA) with several full-duplex decode-and-forward relays. In order to make sure that everyone gets their fair portion of the network's resources, the problem is expressed in a way that the many relays may adjust to maximise the minimum rate that users can achieve while still being fair with their rates. We establish that the optimisation issue is convex and provide a closed-form expression for the relevant allocation factor.

III. PROPOSED STRATEGY

Dataset Selection

- To go to Kaggle and choose the cognitive radio dataset to load.
- The next thing to do is to get the cognitive radio dataset from kaggle source. In other words, it's a business that sells massive amounts of data. Import this data collection into your python workspace.

Dataset Visualization

- Now you may access the dataset files and examine the information in several ways, such as by looking at the spectrum, the bandwidth, etc.
- First, we need to prepare the dataset.
- At this point, having completed the data preprocessing stage, the data is ready for processing in its entirety. Up this stage, any blanks are filled in with a constant value of one or zero, respectively.

Creating a "training" and "testing" dataset

- Part of the final preprocessing of a dataset is splitting it up into a training and testing set. The initial step in machine learning is to train a model using a dataset, and then the model must pass a testing phase using more datasets.

Machine Learning Classification

- Now use machine learning to determine optimal operating conditions. The previous work made use of a variety of methods. We use the SVM and KNN methods, along with other machine learning techniques, to get optimal outcomes in our suggested strategy.

- The following formulae are used to determine the performance metrics in terms of precision, recall, f-1 measure, accuracy, etc.

- For anything to be a genuine positive (TP), both the prediction and the ensuing occurrence must have been accurate.

- If both the prediction and the actual outcome are negative, we have a true negative (TN).

- For an occurrence to be a "false positive," the prediction must be wrong.

- As the name implies, a false negative (FN) occurs when both the prediction and the actual outcome are incorrect.

IV. CHALLENGES

Despite the promising advantages of Machine Learning (ML) techniques in optimizing resource allocation for Non-Orthogonal Multiple Access (NOMA) systems, several challenges must be addressed for practical implementation. These challenges span across computational complexity, real-time adaptability, data requirements, security concerns, and generalization across dynamic wireless environments.

1. High Computational Complexity

ML models, especially Deep Neural Networks (DNNs) and Reinforcement Learning (RL) algorithms, require extensive computations for training and inference. In real-time NOMA applications, the need for rapid decision-making conflicts with the heavy processing demands of ML techniques. Resource-constrained devices, such as Internet of Things (IoT) nodes and mobile devices, may struggle to execute these complex algorithms efficiently.

2. Real-Time Adaptability and Latency Issues

Wireless networks are highly dynamic, with frequent changes in user mobility, channel conditions, and interference levels. ML-based resource allocation models must continuously adapt to these variations in real time. However, traditional ML models require substantial training time, which makes real-time implementation difficult. Reinforcement Learning (RL)-based approaches, while promising, often require extensive exploration before converging to an optimal solution, leading to potential delays in decision-making.

3. Requirement for Large and High-Quality Training Data

ML models rely on vast amounts of training data to learn optimal resource allocation strategies. Collecting and labeling real-world wireless network data is challenging due to privacy concerns, limited availability of large datasets, and variations in network conditions. Additionally, the efficiency of ML algorithms depends on the quality of the training data. Poorly trained models may lead to suboptimal resource allocation, degrading the overall network performance.

4. Generalization Across Diverse Network Scenarios

NOMA systems operate in heterogeneous environments, including urban, rural, and industrial settings. An ML model trained on one specific scenario may not generalize well to others, leading to performance degradation. Ensuring that ML-based resource allocation techniques adapt seamlessly to diverse network architectures, including 5G and beyond (6G) networks, is a significant challenge.

5. Security and Privacy Risks

ML-based resource allocation models are vulnerable to adversarial attacks, model poisoning, and data privacy breaches. Attackers can manipulate the ML training process by injecting malicious data, leading to incorrect resource allocation decisions that compromise network security and quality of service (QoS). Moreover, protecting user data privacy while leveraging ML for optimization remains a critical issue, especially in federated learning-based decentralized NOMA systems.

6. Interference Management in NOMA Systems

Unlike Orthogonal Multiple Access (OMA), NOMA relies on Successive Interference Cancellation (SIC) to decode multiple user signals in the same frequency-time resource. However, imperfect SIC can lead to residual interference, reducing the overall network efficiency. ML models must be carefully designed to balance interference management, power allocation, and user clustering while maintaining computational efficiency.

V. CONCLUSION

Machine Learning (ML) techniques have emerged as powerful tools for optimizing resource allocation in Non-Orthogonal Multiple Access (NOMA) systems, offering improved spectral efficiency, dynamic power allocation, and enhanced user fairness. However, challenges such as high computational complexity, real-time adaptability, data scarcity, security vulnerabilities, and energy efficiency concerns must be addressed for practical implementation. Future research should focus on developing lightweight ML models, integrating hybrid AI approaches, and enhancing interpretability and security to ensure seamless deployment in 5G and beyond (6G) networks. By overcoming these challenges, ML-driven NOMA systems can significantly enhance wireless communication efficiency, enabling intelligent, scalable, and high-performance networks for next-generation applications.

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