Deep Learning for Resource Allocation in NOMA: A Comprehensive Review with Consideration of Classical User Grouping Methods

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Abstract

In next-generation wireless communication, non-orthogonal multiple access (NOMA) emerges as a disruptive technology that allows several users to connect concurrently on a shared time-frequency resource using methods like successive interference cancellation (SIC). Power allocation and user clustering are the main areas of attention for this review, which looks into the optimization of NOMA systems that mostly rely on resource allocation, which is vital to improving their performance. Identifying the optimal resource distribution involves a large computational expenditure because of non-convex optimization problems. The adoption of deep learning techniques for power allocation is explored, addressing the inherent complexity of the optimization problem. Deep learning, adept at learning intricate patterns from data, is positioned as a powerful tool for overcoming computational challenges. The article emphasizes that the future evolution of NOMA-based wireless communication hinges on effectively leveraging deep learning techniques for resource allocation, outlining potential directions for future research, and highlighting deep learning's transformative potential in addressing complex optimization problems in NOMA systems.

Keywords :

Deep Learning, Resource Allocation, Power Allocation, User association, User Clustering, Non-orthogonal multiple access (NOMA), and Deep Reinforcement Learning (DRL).

1. INTRODUCTION

The search for enhanced user experience, greater system capacity, and higher spectrum efficiency has characterized the development of wireless communication networks in recent years. Non-Orthogonal Multiple Access (NOMA) has become a promising paradigm in this context. Presenting questions to established theories about multiple access systems and allowing several users to communicate simultaneously at the same time and frequency[1],[2]. By assigning power to users with different channel conditions on a shared resource block, NOMA's novel technique in the power domain improves radio spectrum usage.

Amid the pursuit of higher throughput and efficiency in 5G networks and beyond, non-orthogonal multiple access has gained prominence, employing a non-orthogonal transmit approach that allocates high power to users with poor channel conditions and low power to those with favorable conditions. This technique leverages methods such as superposition coding to transmit signals through channel [3], and Successive Interference Cancellation (SIC) as fig (1), to recover signals from users with challenging channel conditions [4],[5].

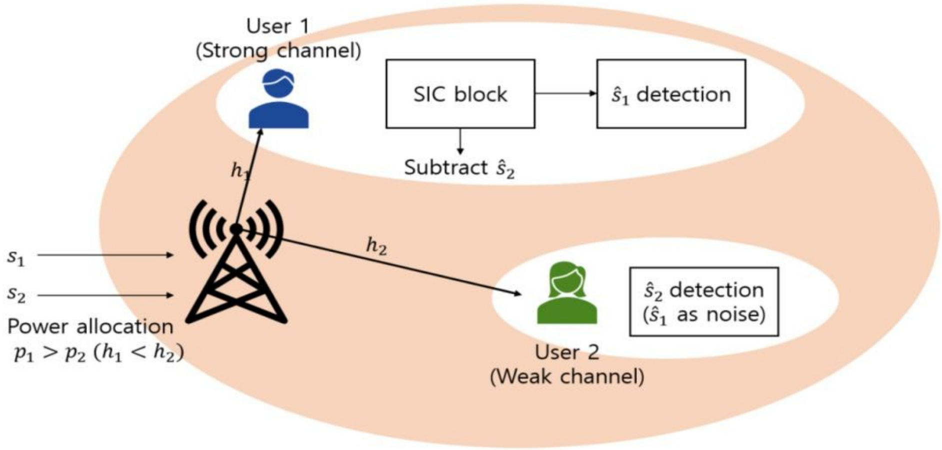

Fig (1) successive interference cancelation [4]

A focal point in NOMA systems lies in resource allocation, intricately divided into power allocation and user clustering. Power allocation [6], determines the distribution of available transmit power among users, impacting system efficiency, while user clustering groups users based on channel characteristics for tailored resource allocation. Conventional power allocation optimization techniques, such as the widely used Weighted Minimum Mean Square Error (WMMSE) method, play a pivotal role. Power allocation poses computational difficulties, characterized as non-deterministic polynomial-time (NP)-hard [7]. Traditional optimization methods have limitations, prompting the exploration of heuristic and suboptimal techniques [7], [8]. However, these methods, characterized by their iterative nature, present computational challenges, necessitating more efficient approaches.

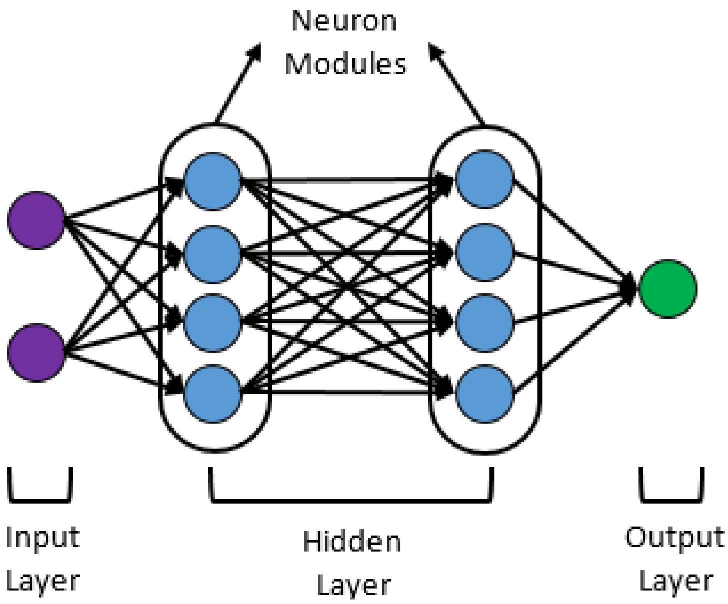

Fig. 2. General basis for deep neural networks [9]

Addressing the critical challenge of power allocation in NOMA systems, this review explores the limitations of traditional optimization methods, which are computationally demanding and often involve heuristic or

suboptimal techniques. The integration of deep learning [9] as shown in Fig 2, methodologies emerge as a transformative solution, capitalizing on non-linear associations in training data to substantially improve system performance. By surveying current research, categorizing approaches, and identifying challenges and future directions, this review aims to provide insights into the potential of deep learning in optimizing resource allocation in NOMA systems, offering a promising avenue for advancing the efficiency and adaptability of wireless networks in the next generation of communication system.

This review focuses on a specific aspect of NOMA's resource management— the integration of deep learning techniques. Deep learning, a subset of machine learning, has demonstrated remarkable success in various domains, and its use in wireless communication systems has drawn more interest. The intersection of NOMA and deep learning opens up new avenues for addressing the intricate resource allocation challenges inherent in NOMA systems.

In this context, the review aims to provide a comprehensive overview of the existing literature on deep learning-based resource allocation schemes in NOMA. By surveying the current state of research, categorizing approaches, and identifying challenges and future directions, this review seeks to contribute to the understanding of the potential of deep learning in optimizing resource allocation in NOMA systems. The exploration of this intersection holds promise for advancing the efficiency and adaptability of wireless networks, paving the way for the next generation of communication systems.

The second section of the paper deals with resource allocation, while the first part deals with power allocation, which reviewed several papers to maximize the total rate. The second part deals with grouping users and reviews several papers that aim to study all the possibilities of grouping users to increase throughput. The third section suggests possible future study directions. The final section is the conclusion.

2. RESOURCE ALLOCATION

Multiple users share a single Resource Block (RB) in NOMA. By selecting appropriate power allocation methods, user interference may be prevented. If not, problems with Power Allocation (PA) and user pairing will surface in terms of resource allocation. To provide fairness of the channel for every user on the transmitter side, when users pair, those with reduced power are assigned higher channel gain and those fewer are assigned to those with more power. The receiver's end of the decoding process becomes more sophisticated as the number of users grows. This is one of the main issues with user matching. Furthermore, if the high- and low-gain users switch to mid-gain users, there will be a reduced channel capacity since mid-gain users are not always paired. [41]

The BS's sent signal may be expressed as

$$x(t) = \sum_{k=1}^{K} \sqrt{\alpha_k P_T} x_k(t) \qquad (1)$$

where $x(t)$ is the total power available at the BS, and α_k is the power allocation coefficient for the UE_k and P_T is the individual information signal.

The received signal at the UE_k is [4]

$$y_k(t) = x(t)h_k + w_k(t) \qquad (2)$$

where h_k is the channel attenuation gain for the link between the BS and the UE_k and $w_k(t)$ is the additive white Gaussian noise at the UE_k with mean zero and density N_0 (W/Hz).

When NOMA is used, the throughput (bps) for each UE can be written as [9]

$$R_k = W \log_2(1 + \frac{P_k h_k^2}{N + \sum_{i=1}^{k-1} P_i h_k^2}) \qquad (3)$$

where W is the available transmission bandwidth and N is the total noise power $N = N_0 W$

2.1 Power allocation

To maximize the benefits of the NOMA system, it is imperative to allocate power efficiently. It has been established that the optimal power distribution issue is NP-hard. Suggesting that examining every potential channel assignment in search of the perfect answer is unfeasible and costly. Researchers have proposed several methods to deal with this problem. power distribution for a downlink Single Input and Single Output (SISO) NOMA system [10], power distribution to provide the most fair allocation of consumers [11], and the most resource-efficient energy usage distribution [12]. Implementing iterative algorithms like WMMSE [13] in actual systems still confronts several significant challenges, even if they perform excellently in delivering high system utility. The high computing cost in real-time is one of the most difficult. Deep learning approaches are required since multiple solutions are suboptimal. It is necessary to employ deep learning techniques since several solutions are subpar. This section will sufficiently offer a comprehensive literature review of deep learning-based solutions to the power allocation problem. Deep neural network generic architecture research using DL in NOMA is at the forefront of recent developments in power allocation technology. Using an Artificial Neural Network (ANN) to manage channel assignment, [14] presents a Deep Reinforcement Learning (DRL) approach to maximize power distribution to consumers. The basis for the system model is a downlink NOMA scenario with BS and many users. Users serve as the deep learning algorithm's performance environment as it treats BS like an agent. BS initially selects a task (channel assignment) from a set before allocating resources and channels to users. After that, a signal of feedback is sent to the BS so that it may utilize the users' replies to allocate people to the next broadcast. The status space, action space, and reward function are the three essential components of this process. The state space is under the control of the channel information. For each user in the action space for data transmission, the agent (BS) chooses a single channel. Every user is linked to a distinct action because the collection of actions is limited to satisfy the needs of user channel allocation. The process of allocation is finished after the user takes action. The reward function is the signal that is returned to the base station (BS) at the end of each time slot, regardless of whether the transmission was successful or unsuccessful. The BS transmits the data, which rates every user's experience, to create the signal. Maximizing this motivational signal and subsequently maximizing each user's data rate is the aim of [15]. The acquired results give a sum-rate comparison between JRA with downlink and JRA with DL; the DL version outperforms the non-DL form by a significant margin. [16] suggests a power allocation system that maximizes the system total rate in a downlink NOMA environment that has an incomplete SIC by utilizing DL methods. The optimal power allocation may be found via an exhaustive approach. To enhance the experience system sum rate, new research [17] suggests a power allocation technique for imperfect SIC. The recommended method makes substantial use of deep learning to forecast the optimal power allocation standards.

In [18], increases the likelihood that every user may effectively decode their desired signals to improve the quality of communication while also guaranteeing user fairness. To reach this, suggested strategies are based on deep learning and divide and conquer. When comparing the two approaches, the earlier is more straightforward and adaptable to the specifics of the system since it obtains closed-form solutions. Better bandwidth use enables the second way to achieve improved performance, even though it does need system training. This approach proposes a dual DNN model to address the issue of noise and unpredictability in training data.

In [19], studies about the joint usage of power optimization and channel estimation-based LSTM for multi-user identification in Power domain NOMA. The impact of DNN in accurately expecting the NOMA cell's client's channel characteristics is investigated in the proposed system, which uses an LSTM network for sophisticated data management to perform training and prediction. The indicated

LSTM-aided NOMA may achieve superior performance measured by the total rate, BER, and outage probability, according to simulation findings. Additionally, users' power factors are tuned to maximize their sum rate, and when the DL technique for channel approximation is used.

In [20], the NOMA system's dynamic user pairing and power allocation methodology have been examined. Split the initial problem into two smaller problems to answer the total sum-rate the ultimate issue of maximizing cellular users. First, the provided sub-channel assignment is used to obtain the closed-form optimum power allocation equation. Next, to create the ideal user pairing scheme, the DQN algorithm is introduced based on the optimal power allocation solution that was found. Ultimately, power allocation and user pairing are combined to find the NOMA system's optimum resource allocation strategy. Simulation findings show that, in comparison to alternative baseline solutions, the suggested scheme can significantly enhance the NOMA system's performance.

In [21], to minimize the system cost, the DQN-based offloading method optimizes the unloading process's transmission power ratio and offloading ratio. Through trials, we evaluated the suggested DQN-based offloading mechanism. The experimental findings demonstrated that, in diverse communication contexts with varying bandwidths, the suggested strategy outperformed other approaches in terms of effectiveness. Furthermore, the suggested DQN-based offloading strategy is more reliable than alternative low-cost techniques in various NOMA-assisted mobile edge computing networks with varying sizes, transmission capacities, bandwidth, or computational capacities. In particular, when there are five sources, the planned technique can reduce In comparison to local computing, the system costs around 15% more.

In [22], the suggested approach begins with a defined range of achievable levels of power and gradually adjusts the search space for power values. The suggested method maintains constant system complexity while optimizing power allocation in a quasi-continuous way through this incremental refinement of the search space. According to the numerical findings, the suggested DRL-power allocation approach performs better in terms of meeting SIC stability requirements and target user rates than the two baseline power distribution methods. It is also the preferred way to handle such a problem since, even with equal satisfaction rates, It achieves more than 85% of the weighted sum rate that a far more complex evolutionary algorithm manages to achieve.

Table 1 provides an overview of the scientific contributions made to DL-based power allocation techniques in NOMA.

Reference No., Year	**Deep Learning Method**	**Model**	**System Description**	**Research Contributions**
[22],2018	Reinforcement	DQN	One base station with N antennas may concurrently communicate with K users using a single antenna.	This algorithm can significantly reduce computational complexity when compared to the strategy where the clustering structure is completely changed even if a single new user arrives.
[23], 2020	Supervised	CNN	CNN-based multi-channel device-to-device communication power control method	Efficiency maximization using power configuration
[24], 2020	Reinforcement	DRL	BS serves a group of K users through a content server. Every user's device has a cache storage installed. Multiple users on a single BS	Indicates that the combination of caching and NOMA improves the usefulness of cache and NOMA. Optimizes the probability that all users will decode desired signals.
[25], 2021	Reinforcement	DQN	k users with single antennas are uniformly distributed around the cell.	Attained 85% of the performance of a complicated genetic algorithm and outperformed two benchmark algorithms.

[26], 2022	Reinforcement	DQL	consists of a Visible light communication (VLC) Access Point (AP) that is raised to a height of L on a ceiling. Single BS multiple users	provide an effective DQL-based method that jointly optimizes the LEDs' transmission direction and power allocation to maximize the average sum rate.
[27], 2023	Reinforcement	DQN-MARL	just one antenna Using Ns orthogonal sub-channels, BS in the cell's center converses with Nu single-antenna Ultra-reliable low-latency communication (URLLC) users. Single BS multiple users	Increase the number of users who are granted access. the suggested DQN-multi-agent reinforcement learning (MARL) system greatly boosts the successful access probability.
[28], 2023	Reinforcement	Deep neural network	BS with multiple antennas and several users using a single antenna	Give a thorough explanation of DL and DRL-based approaches, including CNN, RNN, DQN, and others, that are helpful in the design of physical layer security (PLS) for terrestrial communications in 5G and beyond. Talk about some of the most recent DL frameworks that are out there.
[29], 2023	Reinforcement	DDPG	multi-user NOMA system, where users are dispersed at random around the Base Station (BS), which is located in the middle of the cell.	In comparison to the normal DQN-DDPG, the rate of convergence is nearly doubled and the complexity is increased by 15%. The Prioritized Dueling DQN-DDPG method used around 36% of the time required for the DQN-DDPG algorithm to reach convergence.
[30], 2023	Supervised	DNN	M users are dispersed at random, and the BS is in the middle of the cell.	When compared to FTPA and FPA, DLPA increases the total rate by around 2.2% and 19%.
[31], 2023	Reinforcement	DQN	S sources and one computing access point (CAP) make up a mobile edge computing (MEC) network.	When there are five sources, the developed technique can reduce the system expenses by approximately 15% when compared with local computing.

2.2 User Clustering

It is well-recognized that users are typically dynamic. This makes it difficult to identify each user's signal for NOMA [31]. An adaptive clustering technique can be taken into consideration as a potential fix for this problem. To properly deal with the ever-changing user base of NOMA. To increase efficiency in clustering procedures, the primary issue might be split up and separated into subgroups and groups. This is carried out based on many criteria; these criteria vary according to the approach used and the application circumstances, such as Quality of Service (QoS), locations of users, and the kind of service. The benefits of NOMA and an adaptive clustering technique for various network situations have been covered in earlier research contributions. A two-stage NOMA-based architecture is suggested in [32] to boost fog computing effectiveness. In the first step, users are organized into small groups. In the second stage, power is distributed to every user to further increase network performance. Since single-cell NOMA is all that is used in this model for simulations, QoS is improved over traditional OMA schemes. network performance, users are divided into smaller groups in the first step. In the second stage, electricity is distributed to each user. For this reason, the authors of [33] advise against utilizing traditional mathematical models in favor of artificial intelligence to solve all of the prevalent problems in next-generation networks.

The challenge of appropriately clustering users so that users within one cluster have strong channel correlations and low correlations with other clusters. As a consequence, there will be less interference, which will maximize throughput while optimizing resource usage. The combinatorial character of the clustering problem with more users in the system encourages the application of machine learning techniques to identify the best solution [34].

In [35], we provide a successful ANN-based user clustering NOMA system for varying user counts. The system is trained using the transmitting power and channel gain of NOMA users to determine how to construct user clusters that optimize throughput performance. To attain performance close to optimum throughput, the proposed technique automatically clusters users depending on the decisions made throughout the training phase. The performance of the suggested scheme in terms of throughput and MSE is studied, and the implications of several parameters including learning rates, epoch counts, and user numbers are closely examined. The suggested approach, which achieves a reduced computational complexity while improving the OMA's throughput performance just marginally decreases in comparison to the ideal brute-force method, according to numerical findings.

In [36], examined if deep learning can be used for MIMO-NOMA systems' node clustering. To optimize the sum-rate that results, we have divided the nodes into two distinct clusters using a feed-forward neural network. Using methods from random matrix theory, To develop the training datasets and properly train the learning system, we have produced analytical equations for the sum rates and asymptotic SINRs. According to computer simulation studies, FFNN performs significantly better than PBHC, which is less computationally complex, and its sum-rate performance is extremely near to ideal.

In [28], tries to address the issues of unstable DQN training and poor convergence speed while guaranteeing the system's sum-rate maximization and each user's minimal transmission rate. A suggested approach to resource allocation for the NOMA system incorporates Prioritized Dueling DQN-DDPG joint optimization. To provide the best user grouping strategy, Prioritized Dueling DQN is built using the sum rate as the optimization goal and the current channel status information as the input. The Prioritized DDPG network is used to output each user's power simultaneously during the power allocation phase. The technique uses Temporal-difference error to assess sample relevance and substitutes priority experience replay for earlier randomly dispersed experience replay.

In [29] suggests a novel approach to user grouping to protect users that have similar channel gains from becoming put into the same group, to address the drawbacks of the user grouping is determined by the variation in maximum channel gain. The proposed method improves the system sum rate. For the first time, the DNN in DL is suggested for power allocation to determine the power for every subcarrier. According to the simulation findings, DLPA outperforms fractional transmit power allocation (FTPA)and fixed power allocation (FPA) by around 2.2% and 19%, respectively, in terms of sum rate. The simulation findings show that, in comparison to the FTPA technique, the rate increases by around 10% when the deep learning power allocation (DLPA) method is used among subcarriers and the closed-form expressions (CFE) method is utilized between users.

Table 2 provides an overview of the research contributions made on DL-based user clustering techniques in NOMA.

Reference, No., year	DL Method	Model	System Description	Research Contributions
[22], 2018	Unsupervised	K-mean	Single BS with M antennas with U single antenna users	suggest a low-complexity K-K-means-based online user clustering algorithm. This approach can significantly reduce computational complexity in comparison to the approach that modifies the clustering structure when a single new user joins the system.

[37], 2019	Unsupervised	K-means and K-methods	Using mmWave frequency bands, an aerial base station (ABS) with M antennas may interact with U users using a single antenna.	Demonstrated significant improvements in energy collected performance as compared to conventional OMA-enabled mmWave aerial SWIPT networks.
[35], 2020	Unsupervised	ANN	Single-cell downlink NOMA system using M randomly distributed	Achieve a nearly ideal throughput performance of 98%, which represents a significant decrease in complexity when compared to the best techniques.
[38], 2020	Unsupervised	K-means++	Each UE is a member of just one cluster, which is made up of N UEs.	Developed closed-form formulations for the CFmMIMO- NOMA SSE that account for the impacts of faulty SIC, intra-cluster pilot contamination, and inter-cluster interference.
[39], 2020	Unsupervised	Hierarchical	one base station (BS) with M antennas and N users of a single antenna	Automatic identification of the ideal cluster size. Increase the sum- rate while ensuring that each user has a minimal level of QoS. The number of clusters does not have to be the first argument.
[40], 2020	Reinforcement	state-action reward state-action (SARSA) Q-Learning	resource block at the BS side has multiple-cell NOMA cluster users.	Given a total rate and long-term incentives to assure long-term performance for the resource blocks that are accessible.
[29], 2023	Supervised	DNN	M users are dispersed at random, and BS is at the center of the cell.	An enhanced approach to user categorization is based on the greatest channel gain difference.
[28], 2023	Reinforcement	Dueling DQN	NOMA system with many users, where users are dispersed at random around the Base Station (BS) at the cell center.	When user grouping is done using Dueling DQN, the training process is comparatively stable and the training convergence speed is greatly increased.

3. Future Research

Further studies on enhancing the intelligence, adaptability, and simplicity of NOMA technology. Here are some possible future paths for research on deep learning's use with NOMA systems:

3.1 Innovative Algorithms

Algorithms for unsupervised learning can deal with user clustering. In both static and dynamic situations, user clustering may be accomplished by the expectation-maximization approach. Once it has been learned about the underlying frameworks and correlation between users. NOMA ensures several access points inside a single channel, which reduces the aggregation delay in FL model updates. Furthermore, transfer learning may update partial or entire neural network parameters based on well-trained DRL and DL, with little time and data.

3.2 Multi-Cell NOMA System

The majority of studies in NOMA systems focused on single cells, with relatively few addressing the multi-cell notion due to inter-cell interference caused by the multi-cell system. The weak users' performance at the cell edge will be impacted by the interference. So a small-cell 5G idea must be contained in the multi-cell NOMA system to address the interference concerns as well as the pairing and decoding issues. This is the issue that has to be resolved in the multi-cell NOMA systems in the future.

3.3 Mobility in NOMA

Static systems constitute the main emphasis of the NOMA systems study. Based on the users' stable actions, several algorithms for power distribution, pairing, and SIC receivers are suggested. Future communications will, however, need SIC algorithms, pairing, and dynamic power allocation. The channel gains change depending on the user's position as they go from one place to another. Therefore, one of the topics of future study will be suggesting dynamic algorithms for NOMA systems.

4. Model Selection:

The primary challenge in deep learning-based communication systems is neural network architecture. The potential of deep learning to not only simplify and expedite communication but also lower complexity and thus lower costs makes the search for broad frameworks like long short-term memory (LSTM), which is extensively utilized in natural language processing, essential. Effective and comprehensive models that can handle the problem of power allocation in NOMA are required. An additional approach to resolving resource allocation problems is deep reinforcement learning (DRL). There are many resource allocation and energy management optimization difficulties, including power allocation problems, for the future generation of wireless communication technologies, however, the current state of deep learning and expertise cannot handle enormous volumes of data. Deep learning models (DRL) should be carefully researched for future wireless communications since they are a viable solution to this problem.

5. Methodology

paper ref.	Databases Searched	Keywords Used	Time Frame	Inclusion and Exclusion Criteria	Data Extraction
22	IEEE Xplore	neural network	2010-2023	show that Convolutional Neural Network (CNN)can find out the transmitting power control plan	The deep learning model used (CNN), the specific architecture, and the training process. Also, details about the simulation environment, datasets, and the channel model used in the experiments.
23	IEEE Xplore	power allocation	2015-2023	finding an appropriate power allocation for message signals.	Details on the optimization techniques and the deep reinforcement learning (DRL) model used, including the model architecture, the training process, and the specific environment or simulation setup.
24	IEEE Xplore	Reinforcement learning	2020-2023	They model the problem of maximizing the number of successful access users as a multi-agent reinforcement learning problem.	Details on the MARL approach used, including the type of reinforcement learning algorithm (e.g., Q-learning, deep Q-networks), the agent design, the state and action space, the reward function, and the training process.
25	MDPI	Resource allocation	2020-2023	this paper proposes a user grouping and power allocation method for NOMA systems based on Prioritized Dueling DQN-DDPG joint optimization.	Detailed information on the hybrid DQN-DDPG model used, including the architecture of the DQN (with dueling and prioritization mechanisms), the structure of the DDPG network, the training process, and how these models interact in the context of NOMA resource allocation.

26	IEEE Xplore	deep Q-learning (DQL)	2020-2023	proposes a deep Q-learning (DQL) framework that aims to optimize the performance of an indoor NOMA-VLC downlink network.	Details on the Deep Q-Learning model used, including its architecture, state and action spaces, reward function, and training process
27	MDPI	User grouping	2020-2023	Users are grouped first and then power is allocated. For user grouping, the user grouping method based on the maximum channel gain difference is improved to prevent users with similar channel gains from being grouped together. For power allocation, the deep learning power allocation algorithm is used among subcarriers	The specific methods used for power allocation and user grouping, including any algorithms or optimization techniques.
28	IEEE Xplore	weighted sum-rate maximization	2020-2023	the proposed DRL framework is specifically designed to find a solution with a much larger granularity, emulating a continuous power allocation.	Details on the Deep Q-Learning model integrated with a bisection method, including the model architecture, state and action spaces, reward function, and training process.
29	ScienceDire	deep learning (DL)	2020-2023	They present a detailed analysis of various DL and deep reinforcement learning (DRL) techniques that are applicable to PLS applications.	The approach taken by the authors to gather and analyze the literature, including the criteria for selecting papers, the databases searched, and the keywords used.

35	Archive ouverte HAL	deep learning	2020-2023	user clustering in an uplink multiple input multiple output(MIMO) in NOMA	The specific deep learning model or architecture used for user clustering, such as the type of neural network, its layers, and the training process. Also, details about the data used for training, the simulation environment, and how the MIMO-NOMA system was modeled.
36	IEEE Xplore	power transfer	2015-2023	maximize the harvested sum-power of all EH devices subject to given minimum rate constraints at different ID devices.	Details on the unsupervised learning algorithms used, including their architecture, clustering criteria, and how these algorithms were applied to user clustering in the NOMA-enabled aerial SWIPT context.
37	IEEE Xplore	user clustering (UC)	2020-2023	The formulated optimization problem is highly non-convex, and thus, it is difficult to obtain the global optimal solution. Therefore, we develop a simple yet efficient iterative algorithm for its solution.	The specific learning-based techniques employed, such as supervised, unsupervised, or reinforcement learning algorithms, and how these techniques were applied to user clustering in a cell-free massive MIMO-NOMA setting.
38	IEEE Xplore	unsupervised machine learning	2020-2023	proposed method can maximize the sum-rate of the system while satisfying the minimum QoS for all users without the need of the number of clusters as a prerequisite when compared to other clustering methods	The hierarchical clustering techniques used, the structure of the clustering process, and how these techniques are adapted to the characteristics of mmWave-NOMA systems.

6. CONCLUSION

This paper reviews the literature on deep learning-based NOMA systems and its research contributions. The application of DL approaches demonstrates that because of its powerful learning capacity, DL has a significant influence on resolving the complicated communication problems faced by NOMA systems. We clearly showed that optimizing DL is necessary for the functionality of NOMA-based wireless communication systems. Within this structure, we offer a comprehensive discussion on relevant works and important performance metrics. We also discuss comprehensively in this article the reinforcement learning system and its importance in Resource allocation, as DQN has been used in recent research in Power allocation, where research was reviewed to try to maximize transmission rate according to the constraints of the minimum transmission rate. As for clustering users, research was reviewed that was designed to improve the maximum channel gain differential to avoid grouping users with comparable channel gains. To reduce interference and to increase the possibility of decoding the transmitted signal. We also highlight possible paths for future study to improve the DL algorithms' performance for NOMA systems.

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الخلاصة :

في الجيل التالي من الاتصالات اللاسلكية، يظهر الوصول المتعدد غير المتعامد (NOMA)كتقنية تجريبية تسمح للعديد من المستخدمين بالاتصال بشكل متزامن على مورد تردد زمني مشترك باستخدام طرق مثل إلغاء التداخل المتتالي (SIC).وتخصيص الطاقة وتجميع المستخدمين هما مجالا الاهتمام الرئيسيان لهذا الاستعراض، الذي يبحث في تحسين أنظمة NOMAالتي تعتمد في الغالب على تخصيص الموارد، وهو أمر حيوي لتحسين أدائها .وينطوي تحديد التوزيع الأمثل للموارد على نفقات حسابية كبيرة بسبب مشاكل التحسين غير المحدبة .يتم استكشاف اعتماد تقنيات التعلم العميق لتوزيع الطاقة، ومعالجة التعقيد المتأصل لمشكلة التحسين .يتم وضع التعلم العميق، البارع في تعلم الأنماط المعقدة من البيانات، كأداة قوية للتغلب على التحديات الحسابية .يؤكد المقال أن التطور المستقبلي للاتصالات اللاسلكية القائمة على NOMAيتوقف على الاستفادة بشكل فعال من تقنيات التعلم العميق لتخصيص الموارد، وتحديد الاتجاهات المحتملة للبحوث المستقبلية وتسليط الضوء على الإمكانات التحويلية للتعلم العميق في معالجة مشاكل التحسين المعقدة في أنظمة NOMA.