Deep Learning Approaches for Overcoming Nonorthogonal Multiple Access Challenges in 5G Networks: A Review

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Abstract: Nonorthogonal multiple access (NOMA) is a promising multiple access scheme for 5G wireless networks. However, NOMA faces several challenges that still need to be solved optimally. Deep learning algorithms have been proposed as a potential solution to address these challenges. This review provides an overview of the use of deep learning algorithms to optimize NOMA performance in 5G networks. An investigation is conducted on how deep learning methods are applied in NOMA systems for resource allocation, channel estimation and detection, successive interference cancellation, and user clustering.They can learn optimal user clustering, optimal allocation, and interference alignment strategies, eventually boosting the network performance. In addition, deep learning algorithms can learn the complex relationships between the transmitted symbols and the received signal, leading to accurate detection of the superimposed signals. Opportunities and challenges in NOMA can be identified based on existing research showing how applying deep learning algorithms is better than conventional approaches. The main contribution of this review is to provide insights into the potential of deep learning algorithms to remarkably improve NOMA performance in 5G networks. This article is also a valuable resource for researchers and practitioners interested in using deep learning algorithms for NOMA in 5G networks.

Keywords: NOMA; 5G networks; resource allocation; channel estimation; channel detecting; SIC; user clustering.

1. Introduction

Fifth-generation (5G) networks are the latest generation of wireless communication systems that provide higher data rates, lower latency, and increased connectivity compared with previous generations of wireless networks [1][2]. When 5G is finally implemented, the underlying concepts of cellular technology change drastically, making them incompatible with older generations. For global high-speed coverage and uninterrupted user experience, 5G technology must combine LTE and WIFI networks. Spectrum control must be reexamined and improved for efficient and effective resource usage in the 5G core network, which requires high flexibility and intelligence [3]. A key technology that enables 5G networks to achieve these goals isNOMA. NOMA allows users to simultaneously share the same time–frequency resources, increasing network capacity and spectral efficiency [4]. However, NOMA implementation in 5G networks warrants further improvement. Channel estimation, resource allocation, successive interference cancellation (SIC), and user clustering are considered vital challenges of NOMA [5][6][7].

Accurate channel estimation is essential in NOMA to allocate power and schedule users. Resource allocation is another critical challenge in NOMA because it efficiently distributes frequency, power, and time resources among users. SIC is another challenge in NOMA because it simultaneously decodes multiple signals from different users, requiring sophisticated signal processing techniques. Finally, user clustering is an important challenge in NOMA because it involves grouping users with similar channel conditions and power requirements to maximize system capacity and efficiency. Addressing these challenges requires the development of robust algorithms that can adapt to changing network conditions and mitigate inter-user interference to boost the performance of NOMA in 5G networks and increase network capacity and spectral efficiency.Researchers have turned to deep learning algorithmsas a potential solution to address these challenges. Deep learning is a branch of artificial intelligence that uses neural networks with multiple hidden layers to learn complex patterns and relationships from data [8] and has emerged as a potential solution to the challenges associated with NOMA in 5G networks. Deep learning algorithms have shown promise in various applications, including image and speech recognition, natural language processing, and game playing [9]. They can optimize NOMA performance by addressing the issues that have been solved in conventional ways but still hinder the attainment of optimal performance [10] [11].

This review article discusses deep learning algorithms' potential in addressing the challenges associated with NOMA implementation in 5G networks. First, a brief background of 5G networks and NOMA is provided. Second, an overview of the most famous deep learning models is introduced. Third, a discussion of the challengesrelated to NOMA and the current approaches to addressing these challenges are presented. This review article mainly focuses on using deep learning algorithms for NOMA optimization, including channel estimation and detection, interference management, and user grouping. Finally, the importance of ongoing studies on the significance of deep learning algorithms in enhancing NOMA performance in 5G networks is emphasized as a conclusion.

2. Background

5G networks are the latest generation of mobile communication systems that provide quicker, more dependable, and more efficient connections than prior generations of wireless networks.To achieve these needs, they incorporate cutting-edge technologies, including massive multiple-input multiple-output (MIMO), mmWave communications, and NOMA [12]. NOMA is a promising strategy that can potentially increase 5G networks' spectral efficiency and connectivity. NOMA is a multiple-access strategy that uses superposition coding and SICS to enable several users to share the same time–frequency resource. [13][14]. A simple scenario with a single base station and a downlink NOMA system for two users is shown in Figure 1. To avoid interference, the better-quality signal from User 1 should be decoded, and the messages from User 2 should be filtered out using SIC before User 2's signal is decoded. When comparing users 1 and 2, user 2 has a bigger share of power allocation.In contrast to conventional orthogonal multiple access methods, NOMA employs power or code domain multiplexing to permit simultaneous transmissions, enabling receivers to detect signals with varied power levels or signature sequences [15][16].In case of a large disparity in the quality of the transmission channels available to different users, NOMA is beneficial because it allows users with poor channels to receive signals with less interference.The conceptual frameworks of NOMA are based on superposition coding, which involves simultaneously superimposing and transmitting multiple signals with various power levels or signature sequences.

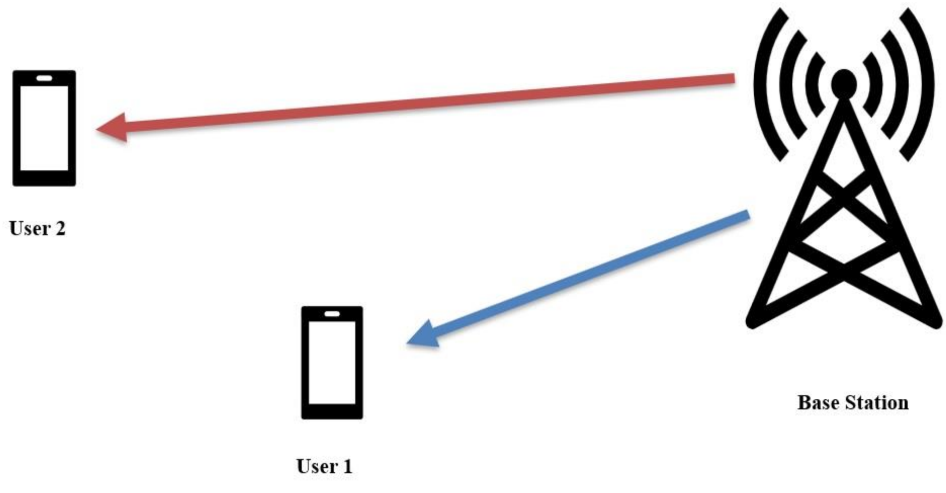

Figure 1. Adownlink NOMA architecture of two users and one base station.

Power and code domains are the main types of NOMA methodologies. The most prevalent version of NOMA, power-domain NOMA, enables several users to use the sametime–frequency resources by giving each user's signal a distinctive power level. Nevertheless, code-domain NOMA employs signature sequences; each user is given a different signature sequence to permit simultaneous communications [15][17].NOMA is actualizedusing a novel interference cancellation method termed SIC. With the SIC approach, the receiver first eliminates interference from the powerful user and decodes its signal. The receiver then discards the strong user's decoded signal in favor of the weak one. This procedure is continuously repeated until all the signals have been detected [18][19].NOMA can significantly enhance the performance of 5G networks by increasing the network's capacity while decreasing the amount of transmit power required. Moreover, it may be used with single-input, single-output, and MIMO systems and provide massive connections.Compared to conventional multiple-access methods, NOMA offers several significant benefits. First, NOMA can potentially improve the spectrum's efficiency by enabling many users to utilize the same frequency band, significantly increasing capacity concurrently. Second, NOMA can potentially increase the network's reliability by delivering improved service to customers with poor reception channels. Third, the network's latency and speed decreasedbecause NOMA allows for the simultaneous service of several customers [15][18][20].Overall, NOMA has emerged as a potential radio access method for enhancing the performance of 5G wireless networks. It has become a subject of interest in academia and industry due to its capacity to serve several customers while using the same time and frequency resources via power- and code-domain approaches. NOMA has become an essential technology for developing successful 5G wireless networks due to its spectrum efficiency, user fairness, and capacity advantages.

3. Deep Learning Algorithms

Deep learning is a subset of machine learning algorithms that uses many hidden layers to perform more complex targets in advance and accurately.Most deep learning techniques use neural network topologies, which is why deep learning models are sometimes called deep neural networks, as shown in Figure 2.Deep learning shows significant potential in handling NOMA system difficulties, such as resource allocation, channel estimation and detection, SIC, and user clustering. Deep learning can assign resources to users depending on their channel conditions, conduct accurate channel estimation and detection, and improve SIC in NOMA systems due to its capacity to learn from vast datasets. Algorithms based on deep learning may cluster users with similar channel conditions to prevent interference and enhance the overall performance of NOMA systems. These advances in deep learning have the potential to substantially increase the spectral efficiency and capacity of future wireless networks. In the following subheadings, a discussion of the most well-known deep learning models applied in 5G networks is provided as follows:

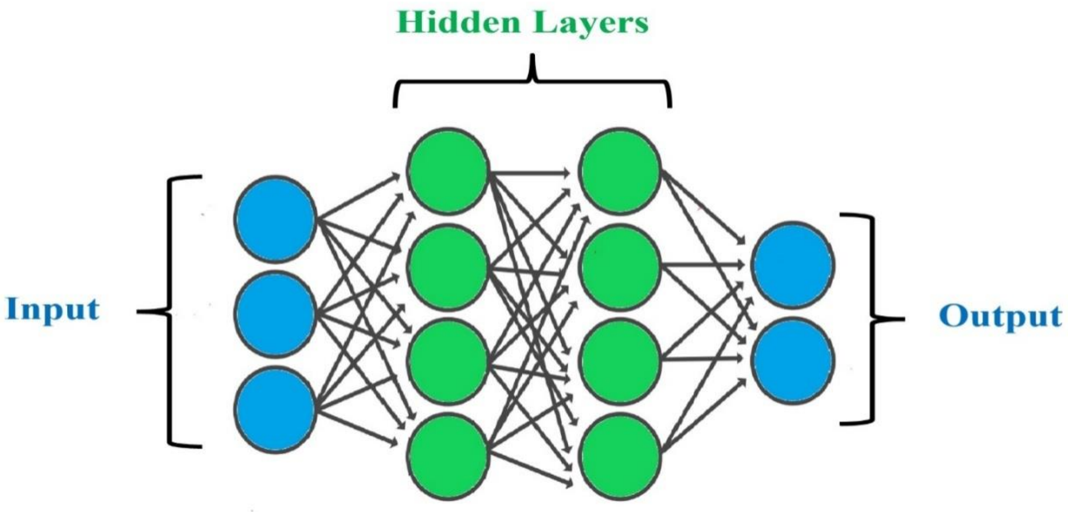

Figure 2.Anarchitecture of deep neural networks

3.1. Convolutional Neural Networks (CNNs)

CNNs have become increasingly popular because of their exceptional performance in image classification, object detection, speech recognition, and natural language processing tasks. One of the critical advantages of CNNs is their ability to learn hierarchical representations of input data by automatically detecting features at different levels of abstraction. This feature allows CNNs to identify complex patterns and relationships in the input data, making the information well-suited for tasks that involve recognizing objects or patterns in images, sounds, or text. CNNs have demonstrated remarkable performance and versatility in various applications, making them a popular choice for many researchers and practitioners in machine learning.

In [21], an innovative approach was presented to parallelize the training of CNNs over several GPUs. A comprehensive overview of current developments in CNNs was conducted in [22]. A new set of rapid algorithms for CNNs were presented in [23] using Winograd's minimum filtering methods. Zhang et al. [24] proposed a CNN-based approach for forest fire detection, trained the model on infrared images of forest areas, and achieved high accuracy in detecting fire occurrences. This efficient and reliable method for early detection could improve forest fire prevention and management. Gopalakrishnan et al.[25] applied transfer learning to CNNs for computer vision-based pavement distress detection. The model was trained on a large dataset of pavement images and could accurately classify different types of pavement distress, such as cracks and potholes. This study demonstrated that transfer learning could significantly improve the performance of CNNs in detecting pavement distress, potentially leading to efficient and cost-effective road maintenance.

Dominguez-Sanchez et al. [26] used CNNs to recognize pedestrian movement direction based on video data. The model achieved high accuracy in predicting the direction of pedestrian movement, showing potential applications in traffic flow analysis and pedestrian safety. In [27], abstract transformers were developed to accurately describe the operation of max pooling, fully connected, convolutional layers. Rectified linear units activate fully connected layers in neural networks. According to [28], the standard practice is to analyze 3D movies frame-by-frame by utilizing 2D convents or 3D perception algorithms.

Nevertheless, they suggested a unique method that uses high-dimensional convolutions in 4D CNNs to analyze these 3D videos for spatiotemporal perception directly. In [29], Context Net was proposed as a novel CNN architecture for automatic speech recognition. Their model incorporates global context information to capture long-term dependencies and outperforms traditional CNN models in speech recognition tasks. Regarding detecting fractures, [30] described a deeply supervised CNN that employs a unique multiscale convolutional feature fusion module.

Overall, these studies showed the versatility and potential of CNNs in various applications, from natural language processing to image and speech recognition, wireless communications, medical image analysis, and solving partial differential equations. CNN development continues to be an active area of research, and these findings pave the way for further exploration and development.

3.2. Recurrent Neural Networks (RNNs)

RNNs have shown great promise in modeling sequential data, such as time series data, speech, and text. RNNs are particularly useful for dealing with sequences of varying lengths and complex nonlinear relationships between sequence elements. The concept of RNNs dated back to the early 1990s [31] butonly began to gain widespread attentionafter the introduction of Long Short-Term Memory (LSTM) networks by Hochreiter and Schmidhuber in 1997 [32]. LSTMs are a type of RNN that overcome the vanishing gradient problem that plagued earlier RNNs, paving the way for developing sophisticated RNN architectures. Researchers have developed many variations and extensions of the basic RNN architecture. Some examples include Gated Recurrent Units (GRUs) [33], CNNs with RNNs [34], and Attention Mechanisms [35]. These variations have strengths and weaknesses and can be applied to sequential data types.

One of the critical advantages of RNNs is their ability to capture long-term dependencies between elements in a sequence through recurrent connections, which allow information to be passed from one-time step to the next. Owing to this feature, RNNs are well-suited to tasks such as language modeling, where the context of a word or phrase can significantly impact its meaning. However, RNNs also have some limitations. One of the main challenges of training RNNs is the difficulty of propagating errors through time, also known as the vanishing gradient problem [36]. As a result, training large RNNs has become a challenge. Another issue is capturing long-term dependencies, which can be crucial in music generation or stock price prediction tasks. Despite these challenges, RNNs have been successfully applied to a wide range of functions, including speech recognition [37], image captioning [38], and machine translation [39].Due to their ability to accurately capture temporal connections and context, RNNs are particularly useful for investigating sequential data. They have produced outstanding results in a wide range of fields, including natural language processing, speech recognition, and image captioning. Although some difficulties remain to be tackled, the development of revolutionary approaches such as LSTMs and GRUs has improved the functionality and learning simplicity of RNNs, paving the way for exciting possibilities in the years to come.

3.3. Deep Reinforcement Learning (DRL)

DRL is a promising technique for addressing the 5G system challenges. It is a subfield of machine learning (ML) that enables an agent to learn the optimum control approach by interacting with the environment and getting feedback in the form of rewards or penalties [40][41][42]. In 5G systems, DRL has been widely used as a solution to a variety of optimization challenges, including those related to resource allocation, mobility, and handover optimization [43],[44],[45].Resource allocation is one domain in 5G systemswhere DRL has been widely applied. For example, resource allocation in 5G heterogeneous networks (HetNets) is complex due to the network's high complexity and the traffic's dynamic nature. DRL has been utilized in various resource allocation approaches, such as energy harvesting, network slicing, cognitive HetNets, coordinated multipoint transmission, and big data [43]. Handover optimization is another domain in 5G systems where DRL has demonstrated strong potential. Handover optimization is crucial in 5G systems because it improves mobility and throughput performance. The handovers between cells in a 5G cellular network have been optimized with the help of DRL [45].DRL has shown great promise to overcome the obstacles to optimization encountered by 5G systems. It has been successfully used in resource management and handover optimization. DRL is expectedto play an increasingly essential role in optimizing and enhancing the performance of 5G systems in the future as these systems continue to advance and grow complicated [46].

4. Challenges in the Application of NOMA in 5G Networks

NOMA has excellent potential to increase 5G networks' spectral efficiency; however, various challenges must be overcometo fulfill its potential. Allocation of resources, channel estimation and detection, SIC, and user clustering are only a few of the significant difficulties NOMA faces in 5G systemsdiscussed in this work.Allocation of resources is one of the primary issues of NOMA systems. Since NOMA permits several users to share a single frequency resource, equitably allocating resources to optimize system capacity is crucial. Many approaches, such as optimization-based algorithms, game theory, and matching theory, have been developed to tackle this issue [47]. Finding the best resource allocation approach is still a subject of continuous research.

Channel estimate and detection is yet another one of the most significant challenges for NOMA. An accurate channel estimate is crucial to separate the signals because NOMA needs to decode simultaneous signals from the same frequency resource. Power-domain NOMA systems often utilize superposition coding at the transmitter and SIC at the receiver [48]. Many techniques have been applied to enhance channel estimation and detection performance.SIC is an essential component of NOMA systems and is used to reduce user interference. Despite its many benefits, the computational complexity of SIC demands careful implementation to prevent inaccuracy.Several techniques, such as adaptive interference cancellation and hybridanalog–digital cancellation methods, have been proposed to improve SIC performance [49].

Another difficulty with NOMA systems is user clustering. Since NOMA enables several users to share a single frequency resource, effective user clustering is crucial to reduce interference and maximize system capacity. Several clustering techniques have been presented, such as graph partitioning and K-means clustering [50]. However, finding the best user clustering approach is still a current research topic. The following subheading discusses how deep learning strategies have been applied in many approaches to improve efficiency and boost performance.

4.1. Resource Allocation

Efficient resource allocation is a critical challenge in 5G networks, and NOMA is a promising technology to enhance spectral efficiency. However, resource allocation in NOMA is complex because multiple users share the same frequency band, resulting in nonlinear interference. Power and subchannels must be allocated to multiple users to achieve optimal performance. Researchers have proposed various resource allocation algorithms, including conventional optimization-based approaches and, recently, deep learning-based approaches, that aim to improve the system throughput, energy efficiency, and user fairness while mitigating user interference. Developing efficient and effective resource allocation techniques in NOMA systems is crucial to realize the full potential of 5G networks and meetingfuture communication demands.Deep learning models have shown promising results in addressing the resource allocation issue in NOMA 5G systems. Traditional optimization-based methods for resource allocation are computationally complex and may not scale well with the increasing number of users and the complexity of the communication scenarios.

By contrast, deep learning-based methods can provide efficient and effective solutions by leveraging the power of deep neural networks (DNNs) to learn complex patterns and relationships from large amounts of data.One of the main advantages of deep learning-based approaches is their ability to handle the nonlinear and dynamic nature of the wireless communication environment, which is challenging to capture with traditional optimization techniques.

Deep learning models can take advantage of the large amounts of data generated in NOMA systems to learn the optimal resource allocation policies that maximize the system performance while minimizing user interference.

Several deep learning-based resource allocation methods have been proposed for NOMA systems, such as DRL, DNNs, and CNNs. These techniques can improve the energy efficiency, throughput, and fairness of NOMA systems while reducing the computational complexity of the optimization problem.Resource allocation in NOMA systems with inadequate SIC was introduced in detail in [51]. The authors presented an approach that uses a deep RNN to address the issue of resource allocation efficiently and effectively. This method yields high spectrum efficiency and connectivity scalability despite the substantial power consumption and poor energy efficiency of using NOMA technology with imperfect SIC.A systematic approach that employs deep learning algorithms for multi-input and multi-output nonorthogonal multiple access (MIMO-NOMA) systems was presented in [52] to maximize cumulative data rate and energy efficiency. The proposed approach, known as CDNN, deals with the problem of power allocation to increase data rates and energy efficiency in MIMO-NOMA networks. Many simulations have shown that CDNN exceeds the performance of conventional tactics, resulting in higher cumulative data rates and energy efficiency.

To address the OFDMA subcarrier assignment and NOMA user grouping problems in downlink video communication systems, [53] proposed deep learning and supervised learning. The authors suggested a conversion procedure that may map the result of the DNN's output layer's sigmoid activation function to either zero (unassigned) or one (assigned), fulfilling two strict requirements. In the experimental stage of the DNN, a non-iterative method produces PSNR performance that is roughly the same (within 0.2 dB) as that from the iterative methods but with less complexity. One study suggested the Deep Q Network (DQN) as a workable model-free solution for NOMA systems [54]. The multi-agent DQN may enhance power transmission, user offloading patterns, and channel resource allocation. Simulation results demonstrated that the multi-agent DQN technique could effectively empower each agent to pinpoint an optimal solution with high accuracy.

To increase cache usefulness and the system's overall efficacy, [55] analyzed the possible advantages of integrating caching with NOMA. The authors proposed two approaches—a divide-and-conquer-based strategy and a DRL approach—to maximize the quality of service for users and assure fairness. Simulation results showed that these strategies work well. They also compared how well these approaches operate. The combined subcarrier assignment and power allocation issue in uplink multiuser NOMA systems were addressed in [56] using a novel two-step approach based on DRL. Compared with conventional approaches, the suggested DRL algorithm offers enhanced energy efficiency over a range of transmit power constraints. The algorithm dynamically governs all users' transmit power, which can also change the resource allocation strategy in response to system feedback.

For near-optimum resource allocation, [57] suggested a DRL framework. The researchers used an attention-based neural network (ANN) to assign channels. The performance results demonstrated that the presented approach performs better than cutting-edge methods and improves system performance. [58] proposed three DRL-based frameworks to simultaneously assign subchannels and power in an uplink multiuser NOMA system. Discrete DRL-based resource allocation, continuous DRL-based resource allocation, and combined DRL and optimal resource allocation are examples of these frameworks. Numerical analysis showed that the suggested frameworks significantly improve the uplink NOMA system's energy efficiency performance while reducing the computational burden. In [59], the authors discussed a reinforcement learning-based power control approach for downlink NOMA transmission that does not rely on previous knowledge of jamming or radio channel characteristics. This work concentrated on power allocation in a NOMA system with multiple antennas when a clever jammer is present. The effect of multiple antennas and radio channel states was discovered when the researchers derived a Stackelberg equilibrium for the anti-jamming NOMA transmission game and the current criteria that ensure its existence. Compared with the conventional Q-learning-based technique, simulation results showedthat the suggested method dramatically enhances the sum data rates of users.

Deep learning-based methods have the potential to revolutionize resource allocation in NOMA 5G systems, providing efficient and effective solutions that can meet the demands of future communication.Table 1 presents an overview of the deep learning models used in state-of-the-art to tackle the resource allocation challenge.

Table 1: Summary of studies that use deep learning in resource allocation approaches.

DL Model	Research Outcomes	Reference Number
RNN	- Better spectrum efficiency and connection scalability.	[51]
DNN	- Higher data rate and energy efficiency than conventional methods. - Roughly matches the convolutional algorithms' average peak signal-to-noise ratio but with less complexity.	[52],[53]
DLR	- Deep Q network solves model-free NOMA system issues. - Improve performance by using total bandwidth. - Achieve higher energy efficiency under different transmission power constraints than other conventional methods. - Able to allocate resources dynamically. - Achieve high data rates without previous knowledge of jamming and channel conditions.	[54],[55],[56], [57],[58],[59]

4.2. Channel Estimation and Detection

Accurate signal detection and channel estimation are among the main challenges in NOMA 5G systems. Accurate channel response estimation is challenging due to the wireless channel's complexity, especially when multiuser interference is present. Conventional detection and channel estimation techniques may need to be more effective in addressing these problems. Recent studies have, however, demonstrated that these problems could be solved using deep learning models. A model that can accurately detect the desired signals and learn the channel characteristics can be trained using deep learning techniques. This model can effectively estimate the channel and detect the signals despite multiuser interference and channel distortions by learning the complex mapping between the received signals and the desired output.

An example of using deep learning-based approaches for the joint optimization of channel estimation and detection processes, where the model is trained on a large dataset of channel and signal pairs, is provided. The model can be used in real-time for accurate and reliable signal detection and channel estimation. Deep learning models can also enhance the performance of conventional channel estimation and detection techniques by including learned features and representations of the signal and channel properties. With these strategies, NOMA 5G systems have achieved significantly improved performance, making them dependable and effective at addressing the problems associated with next-generation wireless communication networks.

A novel and effective method for NOMA utilizing deep learning that can determine wireless channels for NOMA end-to-end was described in [60]. An LTSM network based on DL was integrated into a typical NOMA system so that the suggested technique could automatically identify channel characteristics. Simulated findings showed that the suggested methodology is superior to conventional approaches in strength and effectiveness.Using deep learning approaches to find an ideal decoding order for a NOMA system efficiently, [61] offered a long-term power allocation scheme (DL-PA) in the framework of satellite-based Internet of Things (S-IoT). Relative to the baseline evaluation criteria, including network utility, average arrival rate, and queuing time, the S-IoT NOMA system's efficiency is vastly improved by the DL-PA technique. In addition, the suggested DL-PA methodology excels over the standard approach by delivering a more reliable decoding sequence. Deep learning is an effective and efficient approach for detecting NOMA signals [62]. Owing to channel distortion and multiuser signal interference, the presented DL technique combines channel estimation with the recovery of the intended signal. Extensive performance simulations confirmed that the developed DL method could overcome the challenges caused by channel impairment and produce satisfactory detection results.

A deep learning-assisted receiver for NOMA joint signal detection was introduced in [63]. The DL-based receiver performs channel estimation, equalization, and demodulation in a single pass. The tapped-delay line channel model can show improvement in performance and resilience when using the presented deep learning method. [64]

presented a novel mechanism for signal detection for NOMA uplink receivers using CNNs in a single-shot mode. In training and testing, a three-layer CNN with 32 filters registered a maximum accuracy of approximately 81%. Compared with existing state-of-the-art methods such as least square, minimum mean square error, and maximum likelihood, the proposed technique demonstrated considerable improvement in symbol error rate versus signal-to-noise ratio across a wide range of channel characteristics.In [65], a bidirectional long short-term memory (Bi-LSTM) structure was developed to perform multiuser uplink channel estimation (CE) and detect the initially transmitted signal. The suggested Bi-LTSM model delivers functional gains regarding symbol error rate and signal-to-noise ratio and can retrieve multiuser transmitted bits that the channel has corrupted. It is appropriate for future wireless communication technologies, such as 5G.

In [66], a NOMA receiver based on deep learning that considers channel state information and recognizes the originally sent symbols of numerous users in a single step was proposed. Comparison between the SIC decoding and the DL-based technique reveals the extraordinary symbol detection ability of the latter. DNNs are assessed to directly recover newly transmitted symbols after being trained offline using data generated from channel realizations and labeled symbol data. Deep learning models can be a powerful and effective solution to channel estimation and detecting problems in NOMA 5G systems. They can provide accurate and efficient channel estimation and multiuser detecting capabilities.Table 2 presents an overview of the deep learning models used in state-of-the-art to tackle the channel estimation and detectionchallenges.

Table 2: Summary of studies that use deep learning in channel estimation and detecting approaches.

DL Model	Research Outcomes	Reference Number
LSTM	- Powerful and effective compared to traditional methods. - Recover channel-distorted multiuser transmission signals.	[60],[65]
DNN	- Identify channel distortion and improve detection performance. - Better symbol detecting than SIC. - Optimally decode the satellite-based Internet of Things (S-IoT) NOMA downlink system.	[61],[62],[66]
CNN	- Accomplishes channel estimation, equalization, and demodulation. - Better performance other than traditional approaches.	[63],[64]

4.3. User Clustering

The increasing demand for high-speed data and internet access has led to the development of new wireless communication technologies, such as the 5G network. NOMA is a promising technology that has gained much attention recently due to its high spectral efficiency and ability to support multiple users on the same frequency channel. However, one of the challenges in NOMA systems is user clustering. It refers to grouping users with similar channel characteristics and power allocation, which is essential for optimizing the system performance, minimizing interference, and maximizing the overall system throughput. User clustering is a complex problem in NOMA networks, especially in multicell scenarios. Various factors, such as the number of users, location, and level of interference, influence the network's performance. Traditional clustering methods may be unable to cope with such networks' complexity and dynamics; therefore, new approaches are required to solve this problem effectively. Deep learning is an emerging technique with great potential in solving complex problems in various fields, including wireless communication networks. Deep learning-based solutions for user clustering in NOMA networks have received interest due to their ability to handle the problem's complexity and provide accurate and efficient solutions.

One approach for solving the user clustering issue in NOMA networks was presented in [67]. This novel technique employs artificial neural networks (ANNs) for user clustering in the 5G NOMA downlink. It aims to maintain an acceptable level of complexity while achieving the highest possible throughput performance. Simulation findings indicated that the suggested method considerably decreases complexity with a throughput performance of 98% (almost ideal throughput performance) compared with optimal techniques. The ANN model can be used to anticipate the development of clusters and to assess the model's accuracy using the learned parameters and tweaked hyperparameters. Another approach presented in [68] uses SARSA Q-learning and DRL algorithms to aid base stations in the optimal allocation of available resources to IoT users considering diverse traffic situations. The SARSA Q-learning and DRL algorithms beat orthogonal multiple access (OMA) in simulations, converging to the maximum sum rate. The proposed approach, which uses uplink NOMA methods in multicell systems and user clustering-based resource allocation, effectively maximizes network traffic.

In [69], reinforcement learning (RL) was presented as a novel solution to the problems of user clustering and power allocation in NOMA systems. The Object Migration Automata and one of its versions address the user clustering problem in stochastic contexts. A greedy heuristic is applied to the obtained clusters to derive power allocation. Multiple classification challenges with deep learning were presented in [70] to identify which users must be specified in the initial step of a MIMO-NOMA approach. Second-order channel statistics serve as the foundation for the neural network feed, ensuring its resistance to rapid fading. The suggested deep learning-based technique gives a significant rate advantage over competing methods by eliminating ineffective "lazy" solutions. A DNN-based user clustering technique known as DNN-UC was employed in [71] to effectively represent the intricate link among cluster formation, transmission powers, and channel diversity. The DNN-UC technique is more efficient than the ANN user clustering approach (ANN-UC) because the UC issue is nonconvex NP-complete, and the ANN model can only partially reflect it. The DNN-UC can attain 97% of the throughput of the BF-S approach by tuning the hyperparameters to almost optimal performance. User clustering is an essential issue in NOMA 5G networks that can significantly affect system performance. Deep learning-based approaches, including DNNs, RL, ANNs, and location-aided schemes, have shown great potential in effectively addressing this problem. These techniques can help improve the overall system throughput and minimize interference, leading to good network performance and user experience.Table 3 presents an overview of the deep learning models used in state-of-the-art to tackle the user clustering challenge.

Table 3: Summary of studies that use deep learning in user clustering approaches.

DL Model	Research Outcomes	Reference Number
ANN	- Reached 98% of throughputperformance.	[67]
DRL	- Optimizes network traffic. - Using a greedy heuristic, infer power allocation from the user clusters.	[68],[69]
FNNN	- Outperforms old slow techniques.	[70]
DNN	- Maximize throughput.	[71]

4.4. SIC

SIC is a critical technique in NOMA 5G networks to mitigate interference and enhance spectral efficiency. However, the effectiveness of SIC in NOMA systems is limited by the complexity and accuracy of the detection algorithms used to decode the signals of multiple users.Traditional detection methods, such as ML and Linear Minimum Mean Square Error, can perform well in ideal conditions; however, noise and intersymbol interference compromise accuracy. Moreover, these methods are highly complex when applied to large-scale systems with many users.Deep learning models have emerged as a promising approach for enhancing the accuracy and efficiency of interference management in NOMA networks to overcome these limitations. DNNs can learn the underlying patterns and correlations in the received signals and use this knowledge to improve detection performance and reduce computational complexity.

Several studies proposed deep learning-based SIC methods for NOMA systems. For example, a novel method for SIC using deep learning for NOMA systems was developed in [72]. In contrast to conventional SIC techniques and DL-based approaches, this method uses a separate DNN to decode each user's stream at every SIC stage, yielding an improved bit error rate performance. In addition, this strategy maintains a low level of computational complexity.In [73], a strategy was presented to improve the performance of single base station and multiuser NOMA systems using CNN-based sequential interference cancellation. The suggested plan successfully reduces the losses brought on by SIC flaws. Simulation results showed that the CNN-based SIC scheme could overcome the limitations of traditional SIC methods and provide reliable detection results. Moreover, [74] recommended deep learning approachesto reduce and categorize interference (IN) in NOMA-based systems. They suggested using a DNN to identify and eliminate the damaging effects of IN and another deep learning network to discriminate between high and low levels of IN in NOMA symbols influenced by noise. Both networks would be deep learning networks.[75] developed a new deep learning-based downlink technique for the MIMO-NOMA system. The proposed method enhances the MIMO-NOMA system's precoding and SIC decoding. Numerical results showed that this approach is practical and more efficient than other techniques.

In [76], a deep learning-based receiver technique with soft information (DLSI) was introduced for uplinking MISO NOMA systems where symbols of the transmitted signals are detected sequentially using DNNs. Owing to the included soft information in the SIC stage, which contains more information about the signal than hard decision, error propagation can be mitigated to a low level.Deep learning models can efficiently handle the problem of SICin NOMA 5G networks. The potential of deep learning lies in its ability to learn complex patterns and correlations in the received signals and use this knowledge to enhance the accuracy and efficiency of the detection algorithms. Developing deep learning-based interference management schemes is critical in realizing high-performance, low-latency, and energy-efficient NOMA 5G networks.Table 4 presents an overview of the deep learning models used in state-of-the-art to tackle the user clustering challenge.

Table 4: Summary of studies that use deep learning in successive interference cancellation approaches.

DL Model	Research Outcomes	Reference Number
DNN	- Improves bit error rate while reducing computing complexity. - Identify impulsive noise and reduce its harmful effects. - Reduces error propagation.	[72],[74],[76]
CNN	- Overcome SIC's limitations and produce reliable detection results	[73]
FNN	- Reduces total mean square error by optimizing precoding and SIC decoding.	[75]

5. Conclusion

This article examined the challenges NOMA faces in 5G networks and the potential of deep learning algorithms to address these challenges. It is clearly shown that deep learning algorithms have the potential to improve NOMA performance in 5G networks significantly.In particular, itdiscussed how deep learning algorithms can be used for resource allocation, channel estimation and detection, SIC, and user clustering in NOMA systems.Our review highlighted several opportunities for future research in this area. One potential research direction is the development of deep learning algorithms that can help optimize power allocation and user clustering in NOMA systems. Another direction is the investigation of hybrid NOMA schemes that combine deep learning algorithms with other optimization techniques toimprove network performance further. Research on the practical implementation of deep learning algorithms in NOMA systems, including computational complexity and energy efficiency issues, is also warranted. To point out, deep learning algorithms can address NOMA's challenges in 5G networks and significantly improve network performance. The development and application of deep learning algorithms in NOMA systems are still in their early stages, and continued research in this area is warranted. Nonetheless, the promising results obtained from existing research suggested that deep learning algorithms could play a crucial role in the success of NOMA in 5G networks.

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