Deep Learning Based Non-Orthogonal Multiple Access

Subjects: Engineering, Ocean
Contributor: Syed Agha Hassnain Mohsan , Yanlong Li , Alexey V. Shvetsov , José Varela-Aldás , Samih M. Mostafa , Abdelrahman Elfikky

Non-Orthogonal Multiple Access (NOMA) has become a promising evolution with the emergence of fifth-generation (5G) and Beyond-5G (B5G) rollouts. The potentials of NOMA are to increase the number of users, the system's capacity, massive connectivity, and enhance the spectrum and energy efficiency in future communication scenarios.

NOMA | Successive Interference Cancellation (SIC) | Channel State Information (CSI) | deep learning

1. Introduction

Cellular networks are becoming denser and more sophisticated because of the expansion in demand for wireless services with extremely fast speeds and low latency. One of the main problems cellular network operators have is developing and managing networks with an extensive number of components and characteristics. Consequently, self-organizing networks (SONs) have emerged as crucial components in managing wireless cellular networks [1]. By limiting human involvement in a network through various capabilities, such as self-healing, self-optimization, and self-configuration, SON technology seeks to lower capital and operating costs [2]. A significant use case for self-healing is the control of cell outages. It is applicable to base stations (BSs) that are no longer able to provide services to customers inside their zone, creating a coverage gap in the network [3]. To enhance coverage and capacity, cellular networks are using many accessing techniques like frequency division multiple access (FDMA), time division multiple access (TDMA), code division multiple access (CDMA) and orthogonal frequency division multiple access (OFDMA). These accessing techniques use the concept of orthogonality to reduce the interference between the users, but it also reduces the number of users multiplexed to access the spectrum. To increase the spectral efficiency (SE) of networks and the throughput of cell-edge users by enabling more users as compared to the available orthogonal resources, non-orthogonal multiple access (NOMA) has emerged as a promising technique in 5G networks [4]. NOMA can be integrated with MIMO, cognitive radio (CR), HetNets, milli-meter waves, mobile edge computing (MEC), visible light communication (VLC), vehicle communication, etc. This will provide high spectral efficiency, data rates and massive connectivity and decreases inter-cell interference and intra-cell interference. Initially, NOMA was used with single cells to improve spectral efficiency. The spectral efficiency is increased by increasing the multiplexed users accessing the single channel with different channel gains. NOMA may be an excellent choice for cell outage compensation due to its capacity to improve performance for cell edge users. In this case, the cell edge users that are participating in the compensation procedure are the users who are experiencing an outage (the unsuccessful users). In [5], the authors attempted the first effort to represent the dual issue of unsuccessful user association and power control quantitatively in a NOMA-based cell outage compensation system.

NOMA is divided into the power domain NOMA (PDNOMA) and code domain NOMA (CDNOMA). In PDNOMA, the multiplexing is based on the transmitted power and in CDNOMA, multiplexing is based on code. Along with CDNOMA and PDNOMA, there were other NOMA techniques like signature NOMA (S-NOMA) and compressing-based NOMA (CS-NOMA). In a recent study, the authors investigate the power domain NOMA [4], which divides users into two groups: those close to the network infrastructure, who receive low transmission powers, and those further away, who receive higher transmission powers. It may provide features like fast throughput and minimal lag time in communication, which are necessary for meeting the criteria. The usual successive interference cancellation (SIC) [6] decoding approach is used at the receiver in a NOMA-based system to ensure the system meets the criteria. Multiple user devices increase the complexity of the wireless system in areas such as low-latency real-time transmission, secrecy rate maximization, resource allocation, and signal identification. Cooperative communication has been introduced in NOMA, which refers to the employment of a relay to improve the system's capacity to serve many customers and to increase the transmission area. There are two varieties of cooperative NOMA communication: user-assisted and relay-assisted [7][8]. In relay-aided transmission, an extra relay aids in communication between users; in this scenario, a near user helps a remote user to send data. A relay either decodes the message or transmits it to the recipient as is or amplifies it and sends it on to the recipient as a larger version [9].

Recently, deep learning-based NOMA systems have been utilized in several application scenarios. The field of study known as "deep learning" (DL) allows a system to learn and improve via exposure to data rather than through predetermined rules. Deep learning is a subset of machine learning. It has distinct advantages over traditional machine learning methods, such as being capable of working on huge volumes of data available for analysis purposes from complex networks owing to the growth of network sizes and usages. End-to-end classification solutions are conceivable from these metadata profiles with processing powers of graphic processing units (GPUs). A well-trained system can make sense of whatever data it is fed, extracting relevant information, and using that knowledge to identify and address issues. Researchers may classify DL under three broad categories: reinforcement learning (RL), supervised, and unsupervised [10]. In supervised learning, a system learns how to make decisions based on examples that have already been categorized. Classification and regression are two applications that can benefit from supervised learning. Unsupervised learning permits a machine to carry out judgments considering unlabeled data and uncovers latent structure in an input. Association and clustering issues are common applications of algorithms based on unsupervised learning. Reinforcement learning describes a system's ability to acquire skills via repeated practice. As it learns from its surroundings, reinforcement learning doesn't need any input data to function. Reinforcement learning allows for the fully automatic detection and categorization of signals. Neural networks are used to implement DL algorithms [11]. The hidden layer, input layer, and output layer are the three components of a simple neural network, as shown in **Figure 1**. Deep neural networks (DNN) are so named because they have several hidden layers between the input and output levels.

Neurons serve as the central processing units for each layer of the network. Recurrent neural networks (RNN) and convolutional neural networks (CNN) are two types of DNNs that differ in how they process inputs and generate outputs.

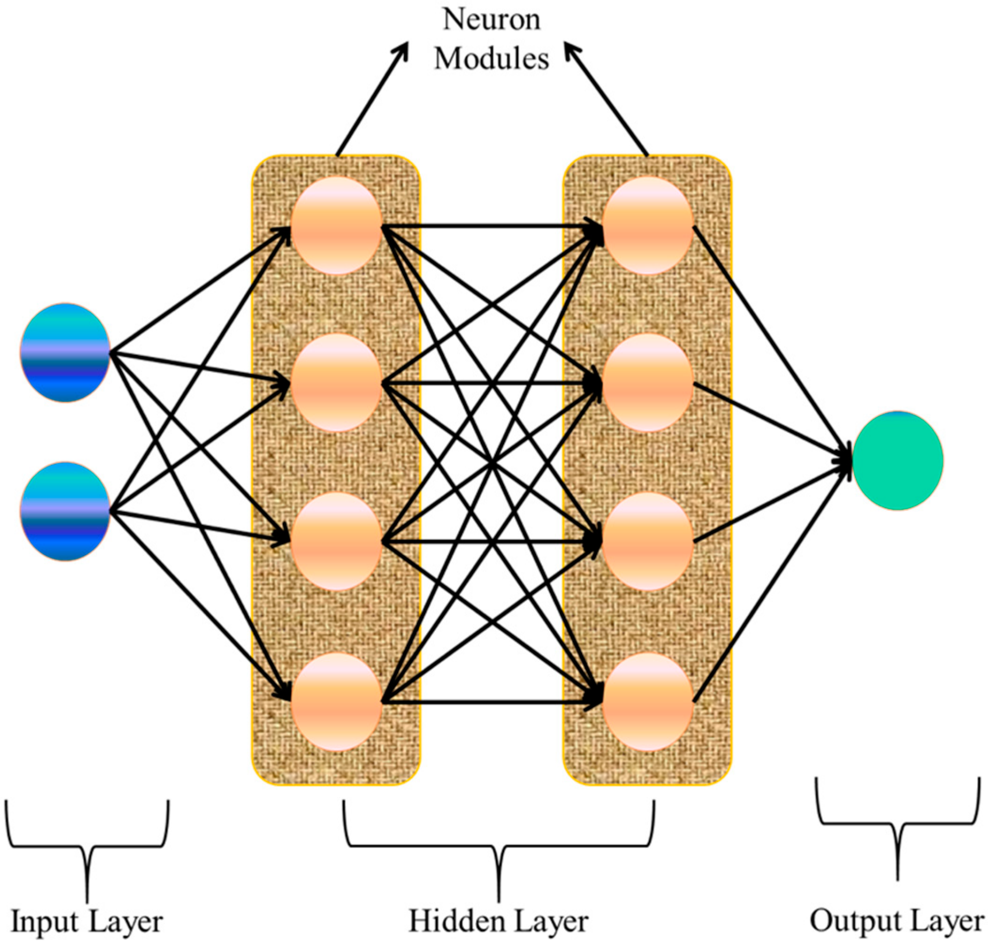

Figure 1. Deep neural network general framework.

Background

Demanding applications such as virtual reality (VR), internet gaming, and high-definition (HD) films have contributed to a burgeoning information explosion [12] during the past decade. The advent of 5G has posed new difficulties in the areas of extensive connection, energy efficiency, peak data throughput, reduced latency, ultra-reliability, and spectral efficiency [13]. The rapid expansion of the Internet of Things (IoT)-based massively heterogeneous networks has necessitated incorporating a number of notable difficulties into 5G technology. Major obstacles to adopting modern multiple access systems now exist due to the uplink or downlink transfer of substantial user data between different networks. NOMA, an intriguing and potential solution for 5G networks, has attracted enormous attention recently [14] as a result of the aforementioned difficulties. Industry and academics alike have recognized NOMA as a promising trend and technology for meeting the varied requirements of 5G. Next-generation mobile or wireless networks rely on this crucial enabling technology to meet the varied demands of users for redundancy, speed, fairness, throughput, and connection. Through signal superposition, NOMA can serve an arbitrary number of users in each resource block.

Additionally, they may allocate power resources to nodes with poor channel characteristics to improve throughput. Compared to traditional multiple access (MA) methods, NOMA makes better use of available resources [15][16]. Unlike NOMA, each orthogonal resource unit in conventional MA techniques serves a single user. This has an adverse effect on the system's overall throughput and spectrum effectiveness. When NOMA is used in these circumstances, it assures that not only users with poor channel characteristics are supplied, but also users with better channel conditions can consume a similar amount of bandwidth as the weak user. The multiuser signals in NOMA are broadcast to the end users after being multiplied in the transmission part through superposition coding (SC) at various power levels based on nonorthogonal symmetry.

Compared to consumers with better channel conditions, those with poorer channel conditions often receive more power. Therefore, having the proper channel state information (CSI) to transmit data has become more important in NOMA. With a strong channel gain, users may readily retrieve the signals gathered in the receiver. Users that experience weak channel capability mistake other signals for interference, which significantly lowers spectral efficiency. With NOMA, in the absence of a guard period and no signal interference, this issue may be solved. NOMA improves user fairness and provides great performance [17].

In contrast to fourth-generation (4G) networks, NOMA in 5G systems is primarily employed to enable larger user density and achieve high spectrum efficiency and low latency [18]. Significantly higher data speeds, increased system capacity, enormous numbers of mobile device connections, decreased latency and decreased power consumption may all be supported by 5G. A wide variety of data transmission entities with various data rates and latency demands make up 5G-enabled systems, including IoT systems. In 5G networks, where several users depend on the same resources, NOMA is employed. In the context of high spectral efficiency and dependable connection among multiple data transmission entities, NOMA in 5G systems is anticipated to satisfy the desiderata of 5G communication systems. Howbeit, NOMA systems have specific drawbacks, including high computational complexity, difficult designs, and issues with resource allocation.

Furthermore, to perform consecutive interference nullification at the receiver side, NOMA systems also need flawless CSI. Perfect consecutive interference nullification is critical for improving NOMA performance. Without understanding the correct CSI at the system's transmitter, it is extremely complex to build a successful power allocation (PA) technique. However, it might be challenging to obtain a near-perfect or flawless CSI. Deep learning (DL) technology may be applied to address all these constraints. The performance of different wireless communication systems is primarily improved by the employment of DL methods. Current communication systems heavily utilize DL-assisted NOMA technologies for a variety of uses. The authors in [19] examine how such systems are used in the literature to assess their contribution to system performance improvement and the various difficulties that arise in such systems when trying to change their design or create technologies optimized for 5G network performance. In recent studies, DL methods have been applied in the NOMA system to enhance the system's functionality. **Figure 2** shows a NOMA-VLC system with a DL-based signal demodulator to successfully attenuate nonlinear and linear distortions.

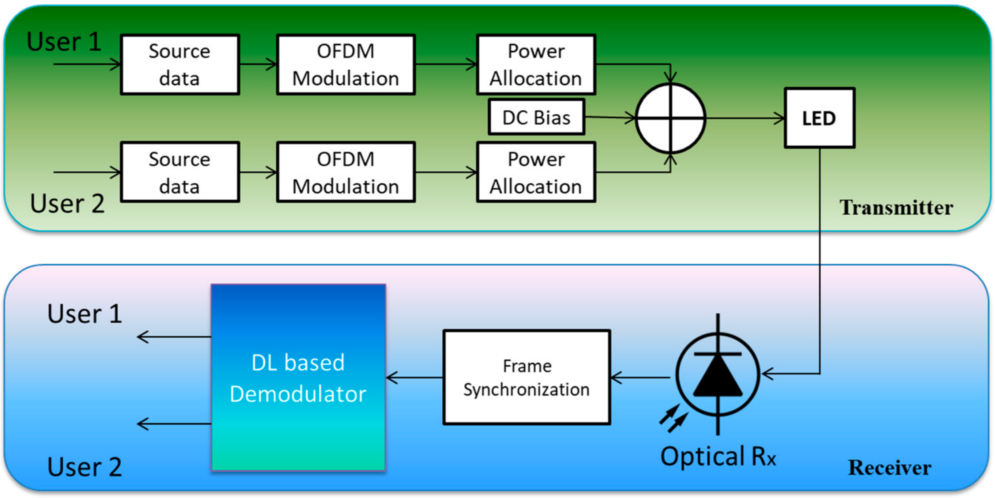

Figure 2. An illustration of DL-based NOMA-VLC system.

2. Key Aspects for Practical Implementation of DL-Based NOMA

2.1. Resource Allocation

In NOMA, one resource block (RB) is shared by multiple users, and the SIC receiver is used to decode the user information at the receiver end based on the user's channel gains. Interference between the users can be avoided by choosing proper power allocation algorithms. Otherwise, resource allocation issues such as user pairing and power allocation (PA) will arise. In user pairing, the users with less power are allocated with more channel gain, and users with more power are allocated with less channel gain to make channel fairness to all the users at the transmitter end. At the receiver end, the SIC receiver is used to decode the same. In this method, if the number of users increases, then the decoding complexity also increases at the receiver end. This is one of the major problems in user pairing. Along with this, another problem, i.e., if the users with high and low gain are transformed to mid-gain, then mid-gain users may be paired or may not, which leads to reduced channel capacity.

To overcome the user pairing issues, optimization techniques, game theory, machine learning and deep learning algorithms are proposed in the literature. The authors proposed an optimization method while pairing two users [20][21][22]. To optimize the user pairing, the channel gain should not be less than the predefined threshold. A strong channel pairing algorithm can increase the system capacity and fairness in user pairing. In [21], the authors used a new pairing concept, i.e., the highest channel gain users are paired with the next highest gain users. Different Game theory algorithms for multiple user pairing and machine learning algorithms for user pairing have been proposed in recent research. In [23], the authors proposed an RL-enabled joint power allocation and user pairing scheme. Through Q-learning, they were able to successfully implement both power allocation and user pairing with reduced computational complexity. In [22], the authors introduced an optimal power allocation technique with a given sub-channel assignment through a closed-form approach. Considering this, a traditional deep reinforcement learning (DRL) algorithm named Deep Q-Network (DQN) algorithm is used to investigate the optimal user pairing scheme. The DQN algorithm provides better performance of the feature extraction ability and higher learning efficiency than conventional reinforcement learning (RL) schemes.

2.2. Power Allocation

One crucial challenge is how to allocate power when there are limited resources to make the most of the benefits of the NOMA system. It has been established that this issue of optimum power allocation is NP-hard, indicating that it is impractical and expensive to study all possible channel assignments to find an ideal solution. As a result, several methods have been put forth by researchers to deal with this issue. Solutions include distributing power for a downlink single input and single output (SISO) NOMA system [24], distributing power for the most equitable distribution of users [25], and distributing power for the most energy-efficient use of resources [26]. Deep learning techniques must be used because several solutions have been demonstrated to be less than ideal. A thorough literature assessment of deep learning-based approaches to the power allocation concern will be provided in sufficient depth in this section. Utilizing DL in NOMA, deep neural network generic architecture efforts are at the forefront of current technological advancements in power allocation. To distribute power to consumers in the best possible way, [27] suggests a deep reinforcement learning (DRL) method; specifically, an artificial neural network (ANN) is employed to perform channel assignment. The system model is based on BS and several users in a downlink NOMA scenario. Users serve as the performance environment for the deep learning algorithm, which treats BS as an agent. To allocate resources and channels to users, BS first chooses a task (channel assignment) from a set. A feedback signal is then provided towards the BS to help assign users in the following transmission based on the users' responses. The three crucial parts of this process are the status space, action space, and reward function. The channel information is responsible for the state space. The agent (BS) chooses a single channel for data transmission for a single user in the action space. The collection of actions is constrained to meet the requirements of user channel allocation, so each user is associated with a unique action. After the user acts, the allocation procedure is complete. The signal returned to the BS as a result of a failed or successful transmission at the conclusion of each time slot is the reward function, as shown in **Figure 3**. The data rates each user experiences and is sent by the BS to make up the signal. The goal of [28] is to maximize this incentive signal and, in turn, optimize each user's data rate. The acquired findings provide a sum-rate comparison of Joint Resource Allocation (JRA) without downlink versus JRA with DL, where the non-DL variant is significantly outperformed by the DL counterpart. [29] suggests a power allocation plan that uses DL approaches to optimize the system sum rate in a downlink NOMA environment with an incomplete SIC. The algorithm for finding the best power allocation is exhaustive. In a recent study [30], a power allocation approach for imperfect SIC to enhance the experienced system sum rate is suggested.

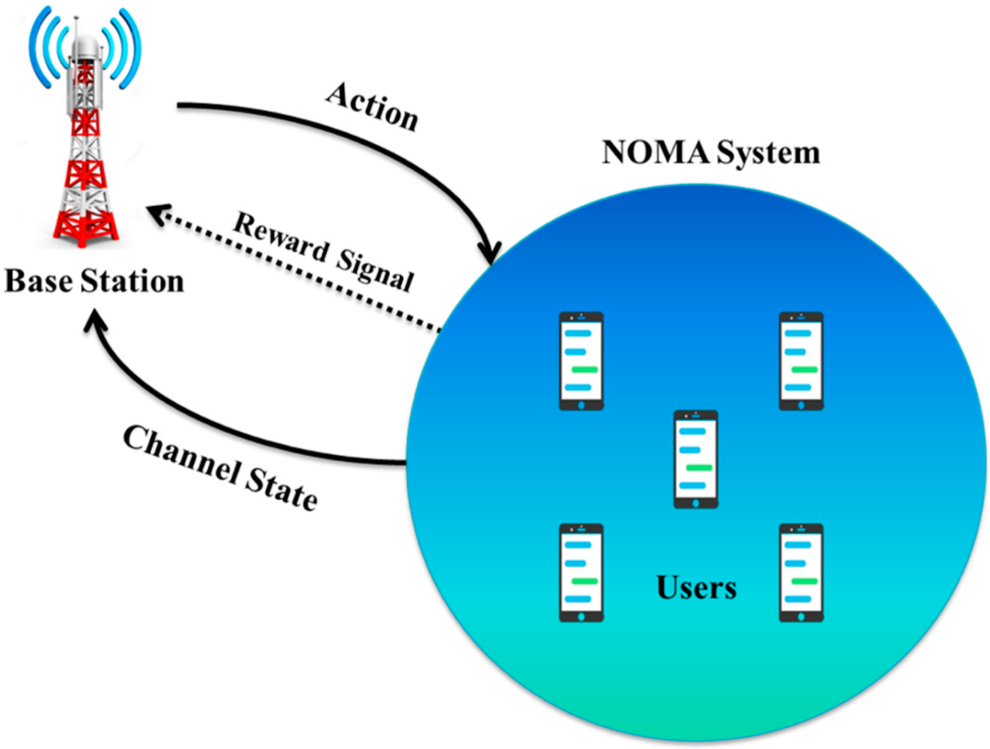

Figure 3. Power allocation and channel assignment of DL-based NOMA system.

2.3. Channel State Information

Practically speaking, channel state information (CSI) significantly influences the NOMA system's performance, and several efforts have been made to implement channel estimation using NOMA scenarios [31]. In [32], a new linear estimator was developed to maximize the average effective signal-to-interference noise ratio (SINR) of the strong user, with a finite SINR required for the weak user to identify the CSI. Meanwhile, several researchers are looking at NOMA-based solutions in various CSI circumstances because the CSI is difficult to collect using conventional approaches. Two power allocation techniques and the performance of NOMA in an incomplete CSI environment were reported [33]. Furthermore, using uplink NOMA systems, the researchers demonstrated that insufficient CSI causes improper decoding and additional interference with the intended signal [34].

Consequently, how to efficiently collect flawless CSI is a crucial challenge in NOMA-aided approaches, and new techniques must be used to address this issue. Although numerous recent research contributions have developed various reliability and sum data rate optimization methods, these techniques demand high computational complexity because of the nonlinear optimization. They are unable to produce an associated power allocation mechanism against a given CSI. In particular, virtually all of the key benefits of NOMA techniques rely mainly on CSI; as a result, several strategies have been presented in previous studies to further enhance the effectiveness of channel estimates [35]. Conventional approaches, however, are unable to trace the alteration in the channel state in real time due to the complexity of the channel conditions in multiple-user systems [36]. Usually, the drastically fluctuating channel characteristics cause CSI acquisition to be disrupted and the NOMA system efficiency to suffer.

Nevertheless, nonlinear reconstruction techniques are inevitable since the channel sparsity trends have been frequently taken for granted in previous studies. Therefore, super-resolution direct arrival (DOA) estimates, and signal identification cannot be accomplished using standard approaches since they are inefficient and unreliable. The NOMA system has recently been enhanced with a promising machine learning (ML) approach to enable the auto-detection of the CSI. The DL [37] idea, introduced in 2006 and a typical branch of machine learning, is a particularly effective technique for managing large amounts of data and resolving challenging nonlinear issues. A few earlier papers [38][39][40][41] included DL in communication in relation to the physical layer, channel coding, and MIMO. The intriguing system that incorporates the DL into the OFDM context has been demonstrated in [42], and its outstanding performance in the context of signal recognition and channel estimation has been confirmed. DL has also been used in traffic monitoring systems, which work admirably [43][44][45]. Additionally, DL-based communication systems have shown certain benefits in terms of security, BER, and throughput performance.

2.4. Successive Interference Cancellation

The drawbacks of SIC might also be addressed using the DL technique. Due to the SIC receiver's poor cancellation, overall capacity decreases [46]. As a result of different hardware limitations, decoding and canceling may be faulty in real-world systems, making SIC possible. The performance gain of NOMA may be enhanced by using SIC at cell-edge users, as demonstrated by the authors in [47]. The creation of an easy-to-use, effective SIC receiver is essential to NOMA. Multi-stage SIC lowers multi-path fading and BER. The performance of the system is impacted by the signal's decoding sequence. High signal-to-noise ratio (SNR) signals are initially deciphered. The performance of the SIC receiver is enhanced by a low complexity, highly effective power allocation algorithm [48]. A real implementation's non-idealities and flaws cause error propagation in SIC, which is utilized to decode and identify desirable signals. Due to the signal processing required for SIC, receiver complexity increases as user equipment (UE) numbers rise. A deep neural network (DNN) is used in [49] to approximate the SIC receiver. In the MIMO-NOMA system, the combined optimization of precoding and SIC decoding minimizes the total mean square error between the user's intended signal and their decoded signal. Users and their sub-bands are grouped according to the status of the channel, ascending. The binary dislocation principle pairs them (BDP). As a result, users with excellent and bad channel conditions will be paired.

A sub-band that satisfies user demands is selected. EP at the receiver can be removed if the signal-to-interference-plus-noise ratio (SINR) difference among a pair of users in the sub-band is sufficiently great. Users that share a band are given authority by BS. The minimum mean square error (MMSE)-SIC method with Interference Rejection Combining (IRC), which analyzes noise and interference independently and enhances average channel capacity and, therefore, system performance, can be used to attain the best performance at the receiver [50]. Some recent works are based on the theory that most EP-related problems in SIC may be handled by appropriately grouping or clustering users. Additionally, by concurrently optimizing precoding and SIC decoding using DNN and domain-specific information, the mean square error (MSE) value between the intended and decoded signals would be reduced to the absolute minimum.

2.5. User Fairness

Several recent studies [51][52] have discussed the benefits of employing NOMA. This increases system throughput, spectrum efficiency and user fairness. Researchers can also obtain an extremely highly reliable connection. Time and frequency resources are distributed to users in the spatial domain through the power domain or code domain NOMA [53]. A recent work [51] uses a deep learning algorithm to ensure user fairness by dividing users into low-rate and high-rate requirement users considering their mobile phone usage habits. The authors consider a NOMA system with DL-based coordinated multi-point (CoMP), used in 5G cellular networks to guarantee the rate requirements from the different edge users. **Figure 4** evaluates the performance of user sum rates in dynamic point selection CoMP (DPS-CoMP) subchannels and the number of cells subchannels. **Figure 4** shows that the user sum rate in the DPS-CoMP subchannel of each cell in the DPA algorithm, the NOMA-CoMP algorithm, and the maximum throughput (MT) algorithm all increase as the number of subchannels increases. In the NOMA power domain, power distribution among users varies depending on the channel characteristics and user-specific channel quality. As a result, consumers located far from the BS will receive more power, and vice versa. According to the works cited in [54], fairness for NOMA in 5G is highlighted by the fact that, in downlink mm-wave NOMA, various data from all users is thus overlaid in the power domain at the transmitter, and the SIC is performed at the receiving side. By integrating SIC and superposition coding (SPC) at the transmitter end and receiver side, respectively, researchers may use NOMA to increase spectral efficiency. The max-min fairness of both the average CSI and instantaneous CSI is also discussed in this literature. Considering the interaction between NOMA and cooperative transmission, the integration of NOMA with several emerging 5G technologies, the correlation with other NOMA variants, and the resource control of NOMA, the authors in [55] focus on state of the art in power-domain multiplexing-based NOMA. Considering the hybrid beamforming system described in the research [55], which employs phase shifters and sets of switches, down-converter, LNA, ADC, and DAC are components of the radio frequency (RF) chain. The price of the system rises along with the number of RF chains. To decrease the number of RF chains, the hybrid beamforming approach is applied, and the system's price will be reduced as a result. 5G deep learning systems have been researched in the literature. Power allocation, DoA estimation [56], physical layer security [57], channel estimation [58], energy optimization, etc., are all included in the program, which significantly addresses user fairness issues in NOMA.

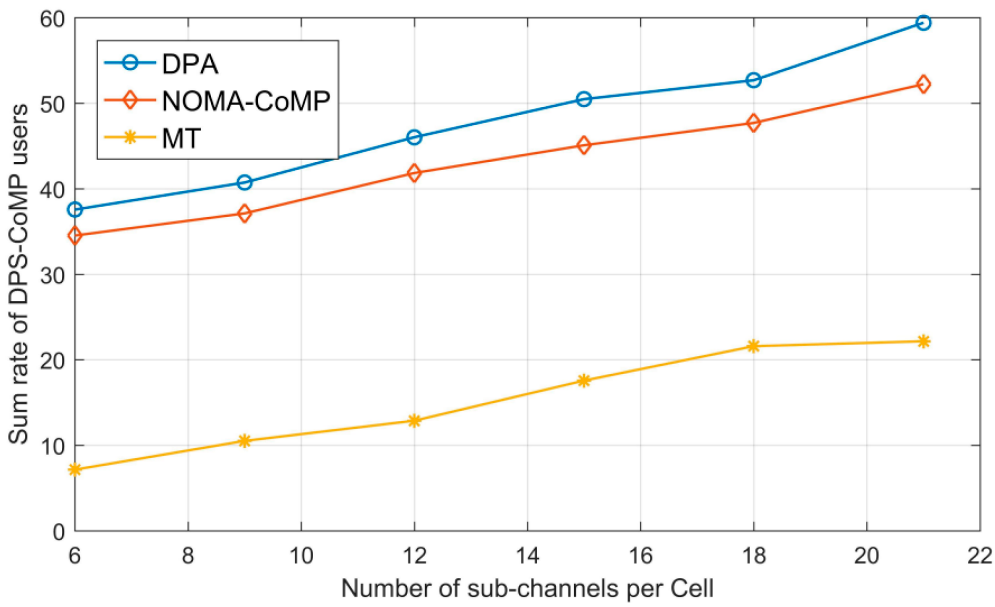

Figure 4. Sum rate of DPS-CoMP users (Mbps) versus the number of subchannels per cell.

2.6. Impulse Noise

2.6.1. Impact of IN in NOMA

Numerous obstacles to the adoption of NOMA systems have been raised by the broader literature on NOMA, which primarily occurs with respect to next-generation networks like the Internet of Things (IoTs) and smart grids. Analysis has also been done on the impact of IN on the NOMA downlink [59][60] and uplink [61] systems. The NOMA uplink systems' outage performance in the occupancy of IN is given in the research work [61]. Analytical findings and comprehensive Monte-Carlo simulations were used to verify the NOMA system's sensitivity to IN. The effect of IN on the cumulative rate capacity of NOMA downlink systems was given by the authors in [60]. The real loss from IN was calculated using a particle IN scenario. The authors also examined how well NOMA performed across Rayleigh-fading channels with composite noise (impulse with AWGN). A union constraint on the bit error rate (BER) was developed using the pairwise loss of bits (LoB) formula. The research study quantified the variance in channel conditions that NOMA users encounter when there is composite noise. The operational reduction of NOMA-aided IoT networks caused by IN was examined, and a mitigation approach was suggested in [62]. For acquired OFDM symbols generated from the power domain multiple-NOMA (PDM-NOMA) strategy, a multistage nonlinear solution based on deep learning was presented.

2.6.2. IN Mitigation Techniques

The threshold-aided IN technique is defined as a memoryless nonlinear mitigation strategy that comprises blanking [63], clipping [64], and clipping/blanking [65]. In this method of mitigation, the high amplitude and short duration of IN are studied by employing a threshold whose adaptation seems difficult. The authors of [66] describe a threshold optimization strategy considering the Neyman-Pearson criteria. In [65], the authors presented a mathematical solution for IN mitigation utilizing clipping and blanking. In [67], a comparison of numerous analog domain processing strategies for IN mitigation demonstrates that threshold value selection is the most important aspect for enhancing the efficacy of threshold-assisted nonlinear techniques. Once the threshold varies due to channel circumstances, the model gets mismatched. As a result, extremely impulsive environments have a negative impact on the effectiveness of all conventional threshold-based approaches. In [59], the authors have successfully used DL approaches for IN mitigation. **Figure 5** presents the DNN performance for IN mitigation in User 1 and compares it with User 2. User 1 uses SIC to reduce inter-user-interference. Thus, it will suffer from IN only. While User 2 is affected by both IN and inter-user interference. Therefore, it has variant BER performance according to SNR values. The results show that the DNN approach can be effectively utilized to overcome IN.

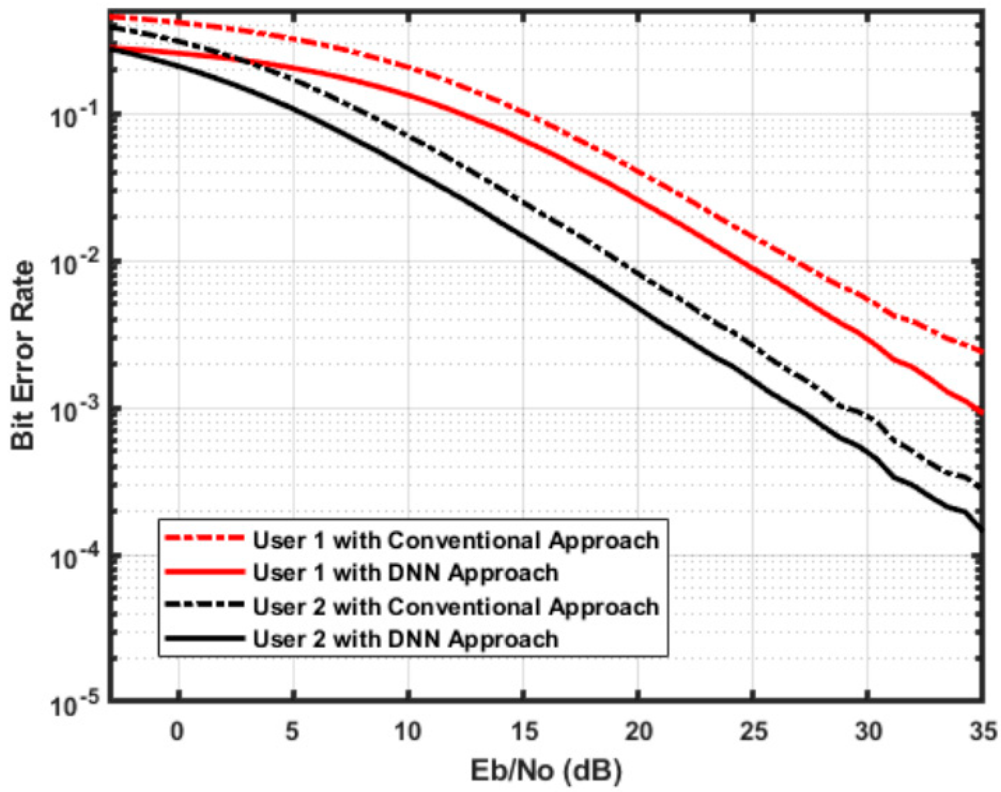

Figure 5. Performance of NOMA user pair through DNN-based technique.

2.7. Transceiver Design

A recent study [68] focuses on explaining how deep learning aids in overcoming the NOMA as mentioned above difficulties. The multiuser receiver (Rx) is initially improved using deep learning from a model-driven and data-driven perspective. The authors briefly explain how deep learning may enable the optimization of end-to-end NOMA transceivers with practical transmitter (Tx) restrictions or domain knowledge. End-to-end learning is used in NOMA to integrate computation and communication. The authors investigate how deep learning can extract and use upper-layer data for transceiver design. They conclude by outlining some exciting new avenues for deep-learning-enhanced NOMA in mMTC.

Multiuser Detection Design [69][70][71][72][73][74][75][76][77]

Different users' signals are sent in a non-orthogonal fashion in NOMA. Generally, multiuser detectors (MUDs) are used at the receiving end to differentiate between the overlapping signal streams, thereby minimising inter-user interference (IUI). For several NOMA systems, state-of-the-art MUDs have been created, including parallel interference cancellation (PIC), sequential interference cancellation (SIC), and message-passing algorithms (MPA). Unfortunately, multi-user detection still lacks a unified signal processing framework. By using DNN to improve MUD, researchers may get a more unified architecture, higher detection accuracy, and shorter processing times. DNN-based concepts may be roughly divided into two distinct camps: data-driven and model-driven. Vanilla DNNs are used in a data-driven strategy, which reduces the time spent on design but increases the amount of data needed for training. Alternatively, a model-driven method uses domain-specific knowledge from NOMA to reduce the need for data and increase learning efficiency. In a recent study [74], the authors propose a DL method that automatically analyzes the CSI of the communication system and detects the original transmit sequences. **Figure 6** shows the symbol error rate (SER) and SNR curve of the numerical simulation. The proposed MIMO-NOMA-DL reached 12.6 dB, whereas the traditional scheme reached 16.2 dB—a difference of approximately 3.6 dB. The authors used powerful DL tools to perform accurate signal detection rather than traditional complex signal processing for channel estimation and demodulation.

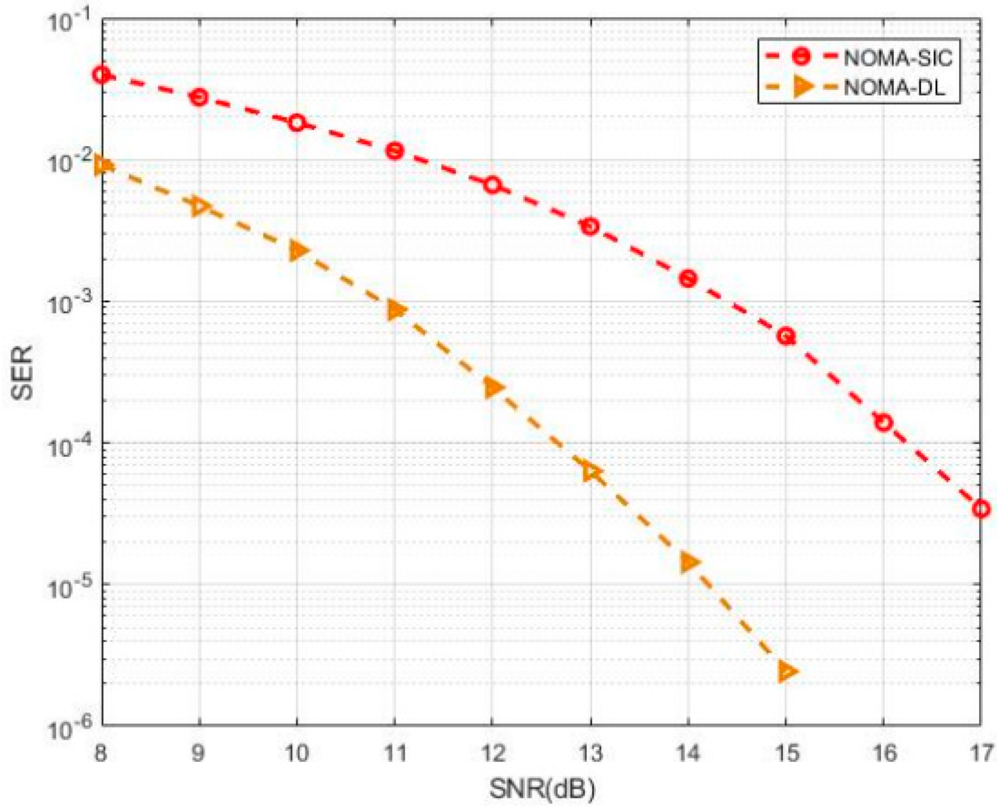

Figure 6. Performance comparison of MIMO-NOMA-DL and MIMO-NOMA-SIC.

2.8. DL for Channel Estimation

In a MIMO-NOMA system, an accurate channel estimate is crucial since it influences the system's performance. Appropriate CSI is necessary for interference cancellation at the receiving end. DNN may be a good option for calculating precise CSI and channel estimates. The researchers of [74] created an algorithm that automatically assesses and seeks the best logical plan for AWGN channels and MIMO Rayleigh fading channel-state information to recover the signal. For every conceivable scenario, including power allocation parameters, it was demonstrated that DL-based approaches might outperform SIC receivers in terms of symbol error rate (SER) performance. Channel estimation and detection were carried out in batches throughout the training phase. In the testing phase, channel error was included, and the authors investigated how the DL method behaved when the estimated CSI and the actual channel state were different. Throughput is decreased because channel estimate errors cause residual and SIC decoding errors. Impact channel estimate error and reference signaling are reduced by the transmission rate back-off method (in which the transmission rate is regulated). Random beamforming is a useful technique for lowering CSI feedback [78]. Since flawless interference cancellation depends on the correct CSI estimate, NOMA system performance is impacted. Practically speaking, it is challenging because of the complicated fluctuations in channel conditions brought on by high mobility. Utilizing the spatial diversity of massive MIMO, DL methods may be utilized to evaluate the DOA and real-time channel estimates. The sparse features may be fully extracted and efficiently used in the DL technique to learn the entire system. DL also performs better than traditional approaches when SNR is high [27].

The articles make it clear that estimate accuracy is a performance parameter and that DL is highly preferred to estimate CSI in real-time with less complexity and pilot overhead than the conventional alternatives. Large datasets with different channel conditions are still difficult for supervised learning, and offline network training takes time. Its efficacy in cases with high mobility is constrained since it is challenging to predict the channel.

2.9. DL for Beamforming and Selection

The performance of 5G technology is also determined by the beamforming process. A quick unsupervised learning-based beamforming design methodology has been put out by authors in [79]. In this approach, DNN is trained offline and provides real-time assistance for simple neural network tasks once it is online. DNN in the downlink records the channel's characteristics, takes the channel coefficients as input, and produces a beamformer. Pruned DNN is used because it decreases the parameters and, as a result, the computational complexity and time required by DNN. The simulations showed that, although degrading with increasing SNR and transmit antenna count, deep neural network performance is comparable to that of WMMSE. In [80], DL-aided hybrid beamforming (HB) is suggested, where supervised learning and an autoencoder build the HB. Compared to other traditional beamforming methods, this approach performed better in the context of bit error rate. A recent study [81] introduces a novel MIMO-NOMA system that addresses partial CSI feedback. Channel quality information (CQI), the best beam, and beam correlation are used to cluster users. The user pair chosen for clustering had the greatest CQI differential and the highest beam correlation. HB is created through clustering. As an analog beamforming vector, the best beam from a high data rate user is selected. Thus, inter-cluster interference is decreased. For weak users, digital beamforming is used to reduce intra-cluster interference. Furthermore, the authors developed a system with efficient power allocation by optimizing the power differential between UEs in a cluster while subject to rate constraints. The system that was presented had a greater sum rate. With DL, choosing a beam is simpler. Using two optimal beam indices as inputs and an estimated power delay profile (PDP) as a label, the DL model is trained using supervised learning. Adam is used for optimization, cross-entropy is utilized as the cost function, and softmax activation is employed at the output layer, where the number of beams equals the number of neurons [82]. DNN may be used to perform beam selection and hybrid beamforming with little latency. Additionally, it produces better results from the perspective of summation rate and BER.

2.10. DL for Modulation and Signal Processing

At high SNR, long-short-term memory (LSTM) and the deep residual network (ResNet) may achieve high classification accuracy. Still, the convolutional long-short-term deep neural network (CLDNN) and ResNet performed well at low SNR. Furthermore, principal component analysis and subsampling were used to minimize training time [83]. In the presence of faulty CSI, CNN for feature extraction and DNN for joint channel equalization and decoding have high accuracy. In terms of BER and decoding rate, DNN outperforms CNN [84]. A system that combines CNN and LSTM is thought to perform well in automated modulation classification (AMC) at varied SNRs [78]. For signal demodulation using Rayleigh and AWGN channels, CNN and a bidirectional gated recurrent unit layer known as a mixed neural network model are utilized. CNN is utilized to extract features, whereas RNN is used for time-series analysis [85]. In [76], the authors propose a deep residual network-based blind modulation detection technique that uses a noisy joint constellation as input. Wavelet denoising is used to increase constellation quality. To demodulate the signal, the SIC receiver at the distant UE requires information on the modulation mode. This technique significantly reduces signaling overhead while improving service quality in NOMA systems. However, for higher-order modulation, the constellation becomes more difficult. A CNN-based AMC with an extended symbol rate sequence and an estimated SNR is a near approximation to a maximum likelihood-based AMC (ML-AMC), learning from raw data and processing in parallel, making it quicker and better than feature-based approaches and ML-AMC [86]. A survey on DL in signal recognition reported in [87] highlighted the difficulty in developing an accurate and effective DL signal recognition system in coexistence. For modulation recognition under various channel impairments and datasets, a modified deep residual network (RN) has been deployed. This outperforms CNN in terms of efficiency. Transfer learning is employed to accelerate the suggested model. In addition, the authors compare the baseline approach and strongly boosted gradient tree classification for radio signal classification utilizing over-the-air observations [88]. In [89], the authors propose employing a single DNN for joint optimum MIMO signal detection and channel decoding. The suggested DNN model has the limitation of requiring training for different channel matrices as well as having a high decoding latency. A DNN that can handle multiple channel matrices with a single training is offered as a research path. For modulation categorization, signal identification, and decoding, prominent models include CNN, RN, LSTM, and customized DNN. In a recent work [90], the authors investigated a deep learning-based SIC scheme for NOMA communication systems and compared its performance with [19] and [91] as shown in **Figure 7**. The authors propose a convolutional neural network (CNN)-based SIC scheme to enhance the single BS and multiuser NOMA scheme. The proposed CNN-based SIC scheme can effectively mitigate losses resulting from imperfections of the SIC. The findings also indicate that the CNN-based SIC method can achieve good detection performance and relieve conventional SIC impairments.

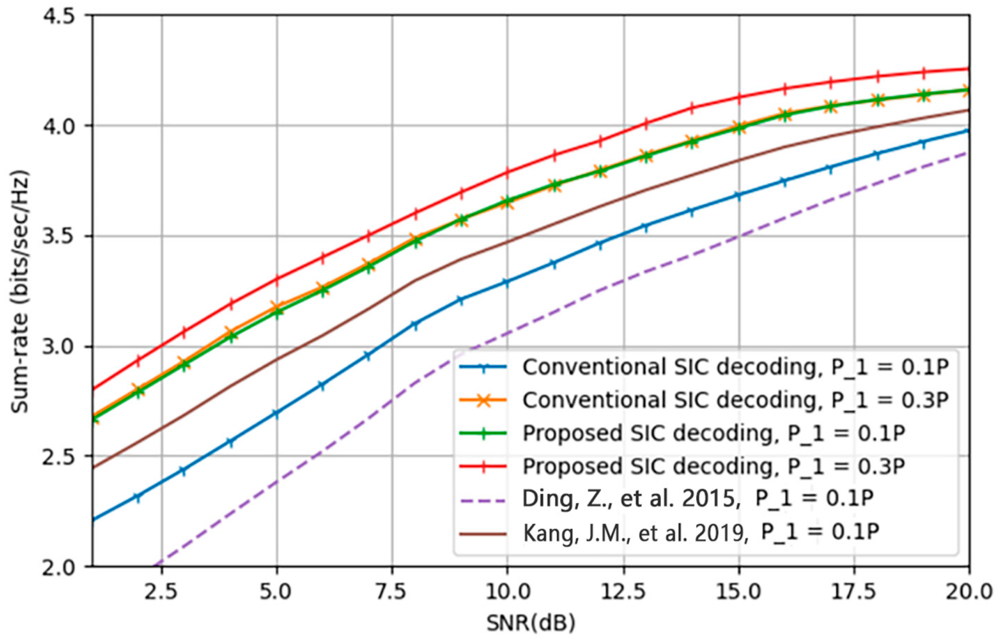

Figure 7. Sum rate versus SNR for the conventional and proposed SIC schemes with varying power allocations.

References

1. 3GPP. Telecommunication Management; Self-Organizing Networks (SON): Concepts and Requirements; 3GPP TS 32.500 V8.0.0; December 2008. Available online: https://www.arib.or.jp/english/html/overview/doc/STD-T63v9_20/5_Appendix/Rel8/32/32500-800.pdf (accessed on 20 November 2022).
2. Aliu, O.G.; Imran, A.; Imran, M.A.; Evans, B. A survey of self organisation in future cellular networks. IEEE Commun. Surv. Tutor. 2012, 15, 336–361.
3. 3GPP. Telecommunication Management; Self-Organizing Networks (SON); Self-Healing Concepts and Requirements; 3GPP TS 32.541 V10.0.0; March 2011. Available online: https://www.etsi.org/deliver/etsi_ts/132500_132599/132541/10.00.00_60/ts_132541v100000p.pdf (accessed on 5 December 2022).
4. Islam, S.R.; Avazov, N.; Dobre, O.A.; Kwak, K.S. Power-domain non-orthogonal multiple access (NOMA) in 5G systems: Potentials and challenges. IEEE Commun. Surv. Tutor. 2016, 19, 721–742.
5. Vaezpour, E.; Majzoobi, L.; Akbari, M.; Parsaeefard, S.; Yanikomeroglu, H. A Deep Learning-Based Approach for Cell Outage Compensation in NOMA Networks. IEEE Open J. Veh. Technol. 2022, 3, 149–166.
6. Su, X.; Yu, H.; Kim, W.; Choi, C.; Choi, D. Interference cancellation for non-orthogonal multiple access used in future wireless mobile networks. EURASIP J. Wirel. Commun. Netw. 2016, 2016,

231.

7. Liu, Q.; Lv, T.; Lin, Z. Energy-efficient transmission design in cooperative relaying systems using NOMA. IEEE Commun. Lett. 2018, 22, 594–597.
8. Ding, Z.; Peng, M.; Poor, H.V. Cooperative non-orthogonal multiple access in 5G systems. IEEE Commun. Lett. 2015, 19, 1462–1465.
9. Hossain, E.; Kim, D.I.; Bhargava, V.K. (Eds.) Cooperative Cellular Wireless Networks; Cambridge University Press: Cambridge, UK, 2011.
10. Pouyanfar, S.; Sadiq, S.; Yan, Y.; Tian, H.; Tao, Y.; Reyes, M.P.; Shyu, M.-L.; Chen, S.-C.; Iyengar, S.S. A survey on deep learning: Algorithms, techniques, and applications. ACM Comput. Surv. 2018, 51, 1–36.
11. Andiappan, V.; Ponnusamy, V. Deep Learning Enhanced NOMA System: A Survey on Future Scope and Challenges. Wirel. Pers. Commun. 2022, 123, 839–877.
12. Index, C.V.N. Global Mobile Data Traffic Forecast Update, 2014–2019; Cisco: San Jose, CA, USA, 2015; White Paper 1 February 2015.
13. Chin, W.H.; Fan, Z.; Haines, R. Emerging technologies and research challenges for 5G wireless networks. IEEE Wirel. Commun. 2014, 21, 106–112.
14. Islam, S.M.; Zeng, M.; Dobre, O.A. NOMA in 5G systems: Exciting possibilities for enhancing spectral efficiency. arXiv 2017, arXiv:1706.08215.
15. Li, A.; Lan, Y.; Chen, X.; Jiang, H. Non-orthogonal multiple access (NOMA) for future downlink radio access of 5G. China Commun. 2015, 12, 28–37.
16. Ding, Z.; Yang, Z.; Fan, P.; Poor, H.V. On the performance of non-orthogonal multiple access in 5G systems with randomly deployed users. IEEE Signal Process. Lett. 2014, 21, 1501–1505.
17. Aldababsa, M.; Toka, M.; Gökçeli, S.; Kurt, G.K.; Kucur, O. A tutorial on nonorthogonal multiple access for 5G and beyond. Wirel. Commun. Mob. Comput. 2018, 2018, 1–24.
18. Wang, Y.; Ren, B.; Sun, S.; Kang, S.; Yue, X. Analysis of non-orthogonal multiple access for 5G. China Commun. 2016, 13, 52–66.
19. Senapati, R.K.; Tanna, P.J. Deep Learning-Based NOMA System for Enhancement of 5G Networks: A Review. IEEE Trans. Neural Netw. Learn. Syst. 2022.
20. Ding, Z.; Fan, P.; Poor, H.V. Impact of user pairing on 5G nonorthogonal multiple-access downlink transmissions. IEEE Trans. Veh. Technol. 2015, 65, 6010–6023.
21. Wang, S.; Lv, T.; Zhang, X. Multi-agent reinforcement learning-based user pairing in multi-carrier NOMA systems. In Proceedings of the 2019 IEEE International Conference on Communications

Workshops (ICC Workshops), Shanghai, China, 20–24 May 2019; IEEE: Piscataway Township, NJ, USA; pp. 1–6.

22. Jiang, F.; Gu, Z.; Sun, C.; Ma, R. Dynamic user pairing and power allocation for NOMA with deep reinforcement learning. In Proceedings of the 2021 IEEE Wireless Communications and Networking Conference (WCNC), Nanjing, China, 29 March–1 April 2021; IEEE: Piscataway Township, NJ, USA; pp. 1–6.
23. Lee, J.; So, J. Reinforcement learning-based joint user pairing and power allocation in MIMO-NOMA systems. Sensors 2020, 20, 7094.
24. He, C.; Hu, Y.; Chen, Y.; Zeng, B. Joint power allocation and channel assignment for NOMA with deep reinforcement learning. IEEE J. Sel. Areas Commun. 2019, 37, 2200–2210.
25. Saetan, W.; Thipchaksurat, S. Power allocation for sum rate maximization in 5G NOMA system with imperfect SIC: A deep learning approach. In Proceedings of the 2019 4th International Conference on Information Technology (InCIT), Bangkok, Thailand, 24–25 October 2019; IEEE: Piscataway Township, NJ, USA; pp. 195–198.
26. Cui, J.; Ding, Z.; Fan, P.; Al-Dhahir, N. Unsupervised machine learning-based user clustering in millimeter-wave-NOMA systems. IEEE Trans. Wirel. Commun. 2018, 17, 7425–7440.
27. Huang, H.; Guo, S.; Gui, G.; Yang, Z.; Zhang, J.; Sari, H.; Adachi, F. Deep learning for physical-layer 5G wireless techniques: Opportunities, challenges and solutions. IEEE Wirel. Commun. 2019, 27, 214–222.
28. Ma, X.; Sun, H.; Hu, R.Q. Scheduling policy and power allocation for federated learning in NOMA based MEC. In Proceedings of the GLOBECOM 2020–2020 IEEE Global Communications Conference, Taipei, Taiwan, 8–10 December 2020; IEEE: Piscataway Township, NJ, USA; pp. 1–7.
29. Xiao, L.; Li, Y.; Dai, C.; Dai, H.; Poor, H.V. Reinforcement learning-based NOMA power allocation in the presence of smart jamming. IEEE Trans. Veh. Technol. 2017, 67, 3377–3389.
30. Elsaraf, Z.; Khan, F.A.; Ahmed, Q.Z. Deep Learning Based Power Allocation Schemes in NOMA Systems: A Review. In Proceedings of the 2021 26th International Conference on Automation and Computing (ICAC), Portsmouth, UK, 2–4 September 2021; IEEE: Piscataway Township, NJ, USA; pp. 1–6.
31. Gui, G.; Huang, H.; Song, Y.; Sari, H. Deep learning for an effective nonorthogonal multiple access scheme. IEEE Trans. Veh. Technol. 2018, 67, 8440–8450.
32. Tan, Y.; Zhou, J.; Qin, J. Novel channel estimation for non-orthogonal multiple access systems. IEEE Signal Process. Lett. 2016, 23, 1781–1785.

33. Senel, K.; Tekinay, S. Optimal power allocation in NOMA systems with imperfect channel estimation. In Proceedings of the GLOBECOM 2017–2017 IEEE Global Communications Conference, Singapore, 4–8 December 2017; IEEE: Piscataway Township, NJ, USA, 2017; pp. 1–7.

34. Gao, Y.; Xia, B.; Liu, Y.; Yao, Y.; Xiao, K.; Lu, G. Analysis of the dynamic ordered decoding for uplink NOMA systems with imperfect CSI. IEEE Trans. Veh. Technol. 2018, 67, 6647–6651.

35. Fan, D.; Gao, F.; Wang, G.; Zhong, Z.; Nallanathan, A. Angle domain signal processing-aided channel estimation for indoor 60-GHz TDD/FDD massive MIMO systems. IEEE J. Sel. Areas Commun. 2017, 35, 1948–1961.

36. O’Shea, T.J.; Erpek, T.; Clancy, T.C. Deep learning based MIMO communications. arXiv 2017, arXiv:1707.07980.

37. Hinton, G.E.; Osindero, S.; Teh, Y.W. A fast learning algorithm for deep belief nets. Neural Comput. 2006, 18, 1527–1554.

38. Wang, T.; Wen, C.; Wang, H.; Gao, F.; Jiang, T.; Jin, S. Deep learning for wireless physical layer: Opportunities and challenges. China Commun. 2017, 14, 92–111.

39. Wen, C.K.; Shih, W.T.; Jin, S. Deep learning for massive MIMO CSI feedback. IEEE Wirel. Commun. Lett. 2018, 7, 748–751.

40. Farsad, N.; Rao, M.; Goldsmith, A. Deep learning for joint source-channel coding of text. In Proceedings of the 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Calgary, AB, Canada, 15–20 April 2018; IEEE: Piscataway Township, NJ, USA; pp. 2326–2330.

41. O’Shea, T.; Hoydis, J. An introduction to deep learning for the physical layer. IEEE Trans. Cogn. Commun. Netw. 2017, 3, 563–575.

42. Ye, H.; Li, G.Y.; Juang, B.H. Power of deep learning for channel estimation and signal detection in OFDM systems. IEEE Wirel. Commun. Lett. 2017, 7, 114–117.

43. Fadlullah, Z.M.; Tang, F.; Mao, B.; Kato, N.; Akashi, O.; Inoue, T.; Mizutani, K. State-of-the-art deep learning: Evolving machine intelligence toward tomorrow’s intelligent network traffic control systems. IEEE Commun. Surv. Tutor. 2017, 19, 2432–2455.

44. Tang, F.; Mao, B.; Fadlullah, Z.M.; Kato, N.; Akashi, O.; Inoue, T.; Mizutani, K. On removing routing protocol from future wireless networks: A real-time deep learning approach for intelligent traffic control. IEEE Wirel. Commun. 2017, 25, 154–160.

45. Abbasi, M.; Shahraki, A.; Taherkordi, A. Deep learning for network traffic monitoring and analysis (NTMA): A survey. Comput. Commun. 2021, 170, 19–41.

46. Sanjana, T.; Suma, M.N. Deep Learning Approaches used in Downlink MIMO-NOMA System: A Survey. In Soft Computing and Signal Processing; Springer: Singapore, 2021; pp. 687–704.

47. Chen, X.; Beiijebbour, A.; Li, A.; Jiang, H.; Kayama, H. Consideration on successive interference canceller (SIC) receiver at cell-edge users for non-orthogonal multiple access (NOMA) with SU-MIMO. In Proceedings of the 2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), Hong Kong, China, 30 August–2 September 2015; IEEE: Piscataway Township, NJ, USA; pp. 522–526.

48. Iraqi, Y.; Al-Dweik, A. Power allocation for reliable SIC detection of rectangular QAM-based NOMA systems. IEEE Trans. Veh. Technol. 2021, 70, 8355–8360.

49. Gao, W.; Han, C.; Chen, Z. DNN-powered SIC-free receiver artificial noise aided terahertz secure communications with randomly distributed eavesdroppers. IEEE Trans. Wirel. Commun. 2021, 21, 563–576.

50. Zhang, H.; Zhang, D.K.; Meng, W.X.; Li, C. User pairing algorithm with SIC in non-orthogonal multiple access system. In Proceedings of the 2016 IEEE International Conference on Communications (ICC), Kuala Lumpur, Malaysia, 23–27 May 2016; IEEE: Piscataway Township, NJ, USA; pp. 1–6.

51. Wu, J.; Sun, L.; Jia, Y. User Pairing and Power Allocation for NOMA-CoMP Based on Rate Prediction. Information 2022, 13, 200.

52. Wong, V.W.S.; Schober, R.; Ng, D.W.K.; Wang, C. Key Technologies for 5G Wireless System; Cambridge University Press: Cambridge, UK, 2017.

53. Chen, X.; Wen, M.; Mao, T.; Dang, S. Spectrum resource allocation based on cooperative NOMA with index modulation. IEEE Trans. Cogn. Commun. Netw. 2020, 6, 946–958.

54. Timotheou, S.; Krikidis, I. Fairness for non-orthogonal multiple access in 5G systems. IEEE Signal Process. Lett. 2015, 22, 1647–1651.

55. Bogale, T.E.; Le, L.B.; Haghighat, A.; Vandendorpe, L. On the number of RF chains and phase shifters, and scheduling design with hybrid analog–digital beamforming. IEEE Trans. Wirel. Commun. 2016, 15, 3311–3326.

56. Huang, H.; Yang, J.; Huang, H.; Song, Y.; Gui, G. Deep learning for super-resolution channel estimation and DOA estimation based massive MIMO system. IEEE Trans. Veh. Technol. 2018, 67, 8549–8560.

57. Do, T.; Le, A.T.; Vahid, A.; Sicker, D.; Jamalipour, A. A Deep Neural Network for Physical Layer Security Analysis in NOMA Reconfigurable Intelligent Surfaces-Aided IoT Systems. J. Latex Cl. Files 2022, 14.

58. Emir, A.; Kara, F.; Kaya, H.; Li, X. Deep learning-based flexible joint channel estimation and signal detection of multi-user OFDM-NOMA. Phys. Commun. 2021, 48, 101443.

59. Hussain, M.; Shakir, H.; Rasheed, H. Deep Learning Approaches for Impulse Noise Mitigation and Classification in NOMA-Based Systems. IEEE Access 2021, 9, 143836–143846.

60. Hussain, M.; Rasheed, H. Performance of orthogonal beamforming with NOMA for smart grid communication in the presence of impulsive noise. Arab. J. Sci. Eng. 2020, 45, 6331–6345.

61. Selim, B.; Alam, M.S.; Kaddoum, G.; Agba, B.L. Effect of impulsive noise on uplink NOMA systems. IEEE Trans. Veh. Technol. 2020, 69, 3454–3458.

62. Selim, B.; Alam, M.S.; Evangelista, J.V.; Kaddoum, G.; Agba, B.L. NOMA-based IoT networks: Impulsive noise effects and mitigation. IEEE Commun. Mag. 2020, 58, 69–75.

63. Yih, C.H. Iterative interference cancellation for OFDM signals with blanking nonlinearity in impulsive noise channels. IEEE Signal Process. Lett. 2012, 19, 147–150.

64. Rožić, N.; Banelli, P.; Begušić, D.; Radić, J. Multiple-threshold estimators for impulsive noise suppression in multicarrier communications. IEEE Trans. Signal Process. 2018, 66, 1619–1633.

65. Oh, H.; Nam, H. Design and performance analysis of nonlinearity preprocessors in an impulsive noise environment. IEEE Trans. Veh. Technol. 2016, 66, 364–376.

66. Ndo, G.; Siohan, P.; Hamon, M.H. Adaptive noise mitigation in impulsive environment: Application to power-line communications. IEEE Trans. Power Deliv. 2010, 25, 647–656.

67. Zhidkov, S.V. Analysis and comparison of several simple impulsive noise mitigation schemes for OFDM receivers. IEEE Trans. Commun. 2008, 56, 5–9.

68. Ye, N.; An, J.; Yu, J. Deep-learning-enhanced NOMA transceiver design for massive MTC: Challenges, state of the art, and future directions. IEEE Wirel. Commun. 2021, 28, 66–73.

69. Kang, J.M.; Kim, I.M.; Chun, C.J. Deep learning-based MIMO-NOMA with imperfect SIC decoding. IEEE Syst. J. 2019, 14, 3414–3417.

70. Thompson, J. Deep learning for signal detection in non-orthogonal multiple access wireless systems. In Proceedings of the 2019 UK/China Emerging Technologies (UCET), Glasgow, UK, 21–22 August 2019; IEEE: Piscataway Township, NJ, USA; pp. 1–4.

71. Jiang, L.; Li, X.; Ye, N.; Wang, A. Deep learning-aided constellation design for downlink NOMA. In Proceedings of the 2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC), Tangier, Morocco, 24–28 June 2019; IEEE: Piscataway Township, NJ, USA; pp. 1879–1883.

72. Miao, X.; Guo, D.; Li, X. Grant-free NOMA with device activity learning using long short-term memory. IEEE Wirel. Commun. Lett. 2020, 9, 981–984.

73. Pan, J.; Ye, N.; Wang, A.; Li, X. A deep learning-aided detection method for FTN-based NOMA. Wirel. Commun. Mob. Comput. 2020, 2020, 1–11.

74. Lin, C.; Chang, Q.; Li, X. A deep learning approach for MIMO-NOMA downlink signal detection. Sensors 2019, 19, 2526.

75. Ye, N.; Li, X.; Yu, H.; Zhao, L.; Liu, W.; Hou, X. DeepNOMA: A unified framework for NOMA using deep multi-task learning. IEEE Trans. Wirel. Commun. 2020, 19, 2208–2225.

76. Xie, W.; Xiao, J.; Yang, J.; Peng, X.; Yu, C.; Zhu, P. Deep learning-based modulation detection for NOMA systems. arXiv 2020, arXiv:2005.11684.

77. Kim, W.; Ahn, Y.; Shim, B. Deep neural network-based active user detection for grant-free NOMA systems. IEEE Trans. Commun. 2020, 68, 2143–2155.

78. Nonaka, N.; Benjebbour, A.; Higuchi, K. System-level throughput of NOMA using intra-beam superposition coding and SIC in MIMO downlink when channel estimation error exists. In Proceedings of the 2014 IEEE International Conference on Communication Systems, Macau, China, 19–21 November 2014; IEEE: Piscataway Township, NJ, USA; pp. 202–206.

79. Huang, H.; Xia, W.; Xiong, J.; Yang, J.; Zheng, G.; Zhu, X. Unsupervised learning-based fast beamforming design for downlink MIMO. IEEE Access 2018, 7, 7599–7605.

80. Tao, J.; Xing, J.; Chen, J.; Zhang, C.; Fu, S. Deep neural hybrid beamforming for multi-user mmWave massive MIMO system. In Proceedings of the 2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Ottawa, ON, Canada, 11–14 November 2019; IEEE: Piscataway Township, NJ, USA; pp. 1–5.

81. Jiang, J.; Lei, M.; Hou, H. Downlink multiuser hybrid beamforming for MmWave massive MIMO-NOMA system with imperfect CSI. Int. J. Antennas Propag. 2019, 2019, 1–10.

82. Ding, Z.; Adachi, F.; Poor, H.V. Performance of MIMO-NOMA downlink transmissions. In Proceedings of the 2015 IEEE Global Communications Conference (GLOBECOM), San Diego, CA, USA, 6–10 December 2015; IEEE: Piscataway Township, NJ, USA; pp. 1–6.

83. Ramjee, S.; Ju, S.; Yang, D.; Liu, X.; Gamal, A.E.; Eldar, Y.C. Fast deep learning for automatic modulation classification. arXiv 2019, arXiv:1901.05850.

84. Chen, Q.; Zhang, S.; Xu, S.; Cao, S. Efficient MIMO detection with imperfect channel knowledge-a deep learning approach. In Proceedings of the 2019 IEEE Wireless Communications and Networking Conference (WCNC), 15–18 April 2019; IEEE: Piscataway Township, NJ, USA; pp. 1–6.

85. Wu, T. CNN and RNN-based deep learning methods for digital signal demodulation. In Proceedings of the 2019 International Conference on Image, Video and Signal Processing, Shanghai, China, 25–28 February 2019; pp. 122–127.

86. Meng, F.; Chen, P.; Wu, L.; Wang, X. Automatic modulation classification: A deep learning enabled approach. IEEE Trans. Veh. Technol. 2018, 67, 10760–10772.
87. Li, X.; Dong, F.; Zhang, S.; Guo, W. A survey on deep learning techniques in wireless signal recognition. Wirel. Commun. Mob. Comput. 2019, 2019, 1–12.
88. O'Shea, T.J.; Roy, T.; Clancy, T.C. Over-the-air deep learning based radio signal classification. IEEE J. Sel. Top. Signal Process. 2018, 12, 168–179.
89. Wang, T.; Zhang, L.; Liew, S.C. Deep learning for joint MIMO detection and channel decoding. In Proceedings of the 2019 IEEE 30th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Istanbul, Turkey, 8–11 September 2019; IEEE: Piscataway Township, NJ, USA; pp. 1–7.
90. Sim, I.; Sun, Y.; Lee, D.; Kim, S.; Lee, J.; Kim, J.-H.; Shin, Y.; Kim, J. Deep learning based successive interference cancellation scheme in nonorthogonal multiple access downlink network. Energies 2020, 13, 6237.
91. Ding, Z.; Adachi, F.; Poor, H.V. The application of MIMO to non-orthogonal multiple access. IEEE Trans. Wirel. Commun. 2015, 15, 537–552.