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SURVEY

An Overview of Deep Learning for Resource Management in mmWave-NOMA

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ABSTRACT Millimeter-wave (mmWave) frequencies ranging from 30 to 300 GHz offer vast bandwidth and high data transmission rates, making them ideal for high-throughput applications and the expanding Internet of Things (IoT). However, mmWave implementation faces challenges such as narrow beams, susceptibility to blockage, and rapid channel fluctuations due to user mobility. To address these issues, non-orthogonal multiple access (NOMA) is employed, enhancing spectral efficiency by allowing multiple users to share the same frequency resources at different power levels. This paper focuses on Power-Domain NOMA (PD-NOMA), a variant of NOMA that allocates different power levels to users sharing the same frequency resources. Although other forms of NOMA, such as Code-Domain NOMA (CD-NOMA) and Cooperative NOMA, exist, our discussion will primarily focus on PD-NOMA due to its practical application in mmWave-NOMA networks. The integration of mmWave and NOMA presents both significant opportunities and complex challenges, particularly in resource management. This combination aims to leverage mmWave's high bandwidth and NOMA's efficient resources utilization to overcome physical layer limitations and enhance network performance. Traditional methods struggle with optimizing those resources like power levels, bandwidth, beam directions, and user pairing. Deep learning (DL) presents a promising solution by learning optimal resource allocation from data. This paper reviews current and future DL applications in five key areas: power allocation, energy efficiency, user association, bandwidth allocation, and subcarrier allocation in mmWave-NOMA networks. It also highlights available open-source datasets, code, and DL frameworks supporting these developments and discusses key research directions. The structure of the paper is organized as follows: first, background knowledge on mmWave and NOMA systems is presented, followed by an in-depth review of DL applications for resource management. Finally, we conclude with challenges and future research directions in this evolving field.

INDEX TERMS Non-orthogonal multiple access, mmWave, deep learning, resource management.

I. INTRODUCTION

Future wireless networks including 6G and beyond, will encounter increasing challenges such as the need for higher data throughput, improved spectral and energy efficiency, greater reliability, extensive connectivity, and comprehensive coverage that spans both terrestrial and non-terrestrial networks. To meet the demands of advanced applications like augmented reality (AR) and virtual reality (VR) in further-enhanced mobile broadband (eMBB), as well as the stringent requirem ents of ultra-reliable and low-latency communication (URLLC) for full automation, industrial control, and connected robotics, and the vast scale of ultra-massive machine-type communication (mMTC) for the Internet of

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Things (IoT), networks must address the growing heterogeneity in quality of service (QoS). The evolution towards 6G is driven by a confluence of existing trends, such as increasing network density and higher data rates, and emerging trends, including new applications and advances in technologies like artificial intelligence, computing, and sensing. To meet the performance targets for 6G, several key trends must be addressed. First, there is a need to achieve significantly higher data rates while ensuring high reliability, particularly at elevated frequencies. This shift necessitates a transition from traditional spatial bandwidth definitions to volumetric ones, which better accommodate the three-dimensional nature of 6G networks. Additionally, the use of electromagnetically active surfaces for communication will be essential. The network infrastructure must also be capable of leveraging both large and small datasets effectively. Furthermore, the evolution from Self-Organizing Networks (SON) to Self-Sustaining Networks (SSN) will play a crucial role. Integration of multiple functions into a cohesive system is necessary to support advanced applications. Lastly, there is a growing shift towards wearable devices and smart body implants, driven by the development of applications such as extended reality (XR) and brain-computer interfaces (BCI). These advancements collectively define the future landscape of 6G, setting the stage for a highly connected and intelligent network ecosystem [1].

To meet these stringent demands, emerging technologies such as millimeter wave (mmWave) communications and non-orthogonal multiple access (NOMA) have been recognized as essential enablers. mmWave communications leverage the abundant bandwidth available in the mmWave spectrum (30-300 GHz) to achieve multi-gigabit-per-second data rates. The broad spectrum available in the mmWave band holds significant potential for achieving high data throughput and minimizing transmission latency [2], [3], [4]. Conversely, NOMA enhances spectral efficiency by enabling multiple users to share the same time-frequency resources through power-domain multiplexing, with successive interference cancellation (SIC) implemented at the receivers [5].

The synergy of mmWave technology and NOMA has garnered significant attention recently as a key enabling strategy due to their ability to provide extensive bandwidth and high spectral efficiency (SE) [6]. However, the integration of mmWave and NOMA technologies introduces significant challenges in resource management. The high propagation losses and sensitivity to blockages in mmWave frequencies necessitate highly directional beamforming and frequent beam tracking/realignment. Additionally, the non-orthogonal nature of NOMA introduces inter-beam and inter-cluster interference, which must be carefully managed through efficient user clustering, power allocation, and interference cancellation techniques. Furthermore, the joint optimization of multiple resources, such as power, subchannels, beamforming vectors, and user clustering, is a high-dimensional and non-convex problem, making it challenging for traditional model-based optimization approaches.

Deep learning (DL) has become a promising method for resolving the resource management challenges in mmWave-NOMA networks. By capitalizing on their capacity to learn intricate patterns directly from data, DL can effectively optimize resource allocation policies without relying on explicit channel models or making simplifying assumptions. Deep neural networks (DNN), convolutional neural networks (CNN), recurrent neural network(RNN), deep reinforcement learning (DRL), and other DL architectures have been explored for various resource management tasks, such as user clustering, power allocation, subchannel assignment, and hybrid beamforming in mmWave-NOMA systems.

This study hypothesizes that DL techniques can optimize resource allocation in mmWave-NOMA systems, significantly improving both spectral and energy efficiency while maintaining system scalability in fast-varying wireless environments.

Although several studies have explored the applications of deep learning in wireless networks, few have provided a comprehensive review of its role in managing resources specifically for mmWave-NOMA systems. This paper aims to fill this gap by reviewing state-of-the-art DL approaches for power allocation, user association, energy efficiency, and bandwidth allocation in mmWave-NOMA networks. The novelty of this work lies in its detailed analysis of DL frameworks and the challenges involved in optimizing resource management, as well as its exploration of open-source datasets, frameworks, and future research directions.

A. RELATED SURVEY

The importance of DL and recent advancement in DL-based resource management in mmWave-NOMA has garnered significant attention from researchers, prompting several surveys being conducted as depicted in Table 1. Here, we highlight the importance and recent advancements in this field based on the insights from various surveys.

Hasan et al. in [7] covered the utilization of DL to enhance the performance of NOMA. Elsaraf et al. in [8] surveyed power allocation using deep learning in NOMA system. Kaur et al. in [9] provided a current overview of emerging wireless system concepts like 6G and the role of Machine Learning (ML) in these future wireless networks. Sharma and Kumar in [10] outlined the key aspects of physical layer security (PLS) where deep learning DL can be leveraged to bolster the security of wireless networks. Bartsiokas et al. in [11] provided an overview of the latest ML approaches for efficient radio resource management in 5G and next-generation networks.

Gupta et al. in [12] provided a solution taxonomy for several resource allocation systems that take into account ML, DRL, graph theory, game theory, NOMA, and joint resource allocation. Khan et al. in [13] introduced the impact of ML techniques on next-geneation wireless networks. Lu et al. in [14] provided a comprehensive survey on the RL based 6G physical cross-layer security and privacy protection.

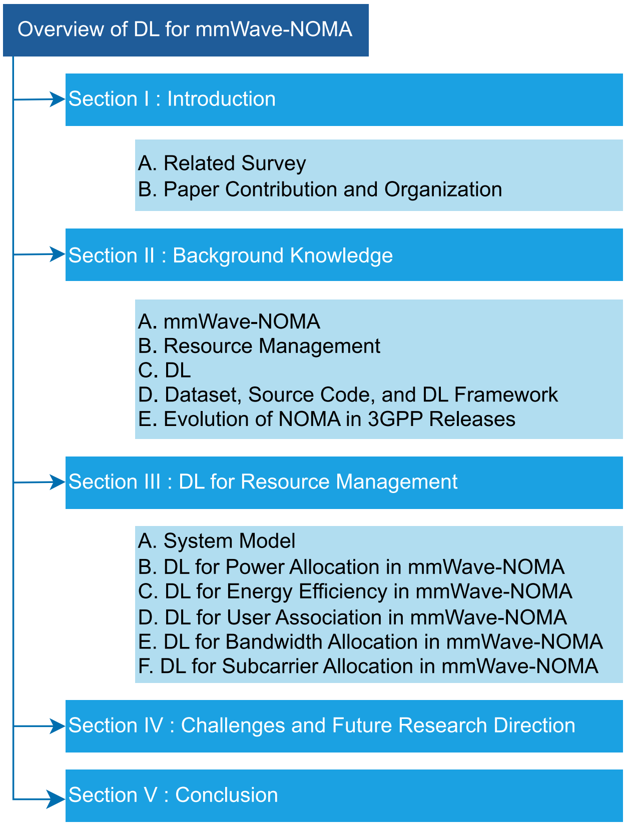

FIGURE 1. Organization of this paper.

Qurratu et al. in [15] provided an overview of ML algorithm for beam tracking techniques. Huynh et al. in [16] conducted a comprehensive analysis of the applications of Generative AI (GAI) in physical layer communications, covering a wide range of conventional problems such as channel estimation, signal classification, and equalization.

Mayarakaca and Lee [17] reviewed the implement of ML on NOMA for UAV communications and Ye et al. in [18] offered insights into AI-enhanced designs for fundamental physical-layer components, such as coding, modulation, multiple access, MIMO, channel estimation, and relay transmission. While extensive surveys exist on DL applications in various domains, a dedicated study focusing on DL for resource management in mmWave-NOMA networks, encompassing power allocation, energy efficient, user association, bandwidth allocation, and sub-carrier/sub-channel allocation, appears to be missing from the literature. This gap motivated us to undertake this comprehensive survey, aiming to explore the potential of DL in optimizing resource management and unlocking the full potential of mmWave-NOMA networks.

B. PAPER CONTRIBUTION AND ORGANIZATION

The key contributions of this survey are outlined as follows.

- Review recent research on DL implementation to optimize power allocation, energy efficiency, user association, bandwidth allocation, and subcarrier allocation in mmWave-NOMA Networks.
- Summarize open dataset, source code, and DL framework related with DL implementation in context of resource management within mmWave-NOMA networks.
- Highlights the trends and future research directions for applying DL for mmWave-NOMA in context of resource management.

The remainder of this paper is structured as follows, as shown in Figure 1. Section II provides a brief overview of the foundational concepts necessary for this survey, including mmWave NOMA systems and DL. Section III reviews recent research on the application of DL in areas such as power allocation, energy efficiency, user association, bandwidth allocation, and subcarrier allocation, respectively. Section IV offers a critical analysis of current trends and potential future directions in this developing field. Finally, Section V contains the concluding remarks. For ease of reading, a list of commonly used acronyms is provided in Table 2.

II. BACKGROUND KNOWLEDGE

A. MMWAVE NOMA

The future 6G era, envisioned to be deployed in the 2025-2035 timeframe, strives to extend the limits of wireless communication beyond those established by its 5G predecessor [19]. The system will function within the 100 GHz to 1 THz frequency band, which includes a portion of the mmWave spectrum. The mmWave spectrum spans from 30 GHz to 300 GHz, featuring wavelengths ranging from 10 mm to 1 mm. These shorter wavelengths enable higher data transmission rates exceeding 100 Gb/s. This extremely high data rate will facilitate ultra-fast downloads for applications such as computers, autonomous vehicles, and robotic controls [20].

As depicted in Figure 2, this ultra-high data rate capability makes mmWave especially suitable for a variety of demanding applications. For instance, it can efficiently support large-scale events where thousands of users require simultaneous connectivity. Moreover, mmWave is integral to the deployment of massive IoT (Internet of Things) devices, facilitating real-time communication and data exchange in environments such as smart cities and smart energy systems. It also plays a crucial role in vehicle communications and transport infrastructure, where high-speed data transfer is essential for the development of autonomous vehicles and advanced transportation systems. Additionally, mmWave technology is utilized in environmental monitoring, enabling the collection and analysis of large volumes of data quickly and reliably, thereby contributing to the advancement of smart city initiatives and increased residential connectivity.

The use of mmWave and THz frequency bands above 100 GHz may necessitate innovative approaches to front-end design, particularly when considering the need to connect a million devices simultaneously in future networks.

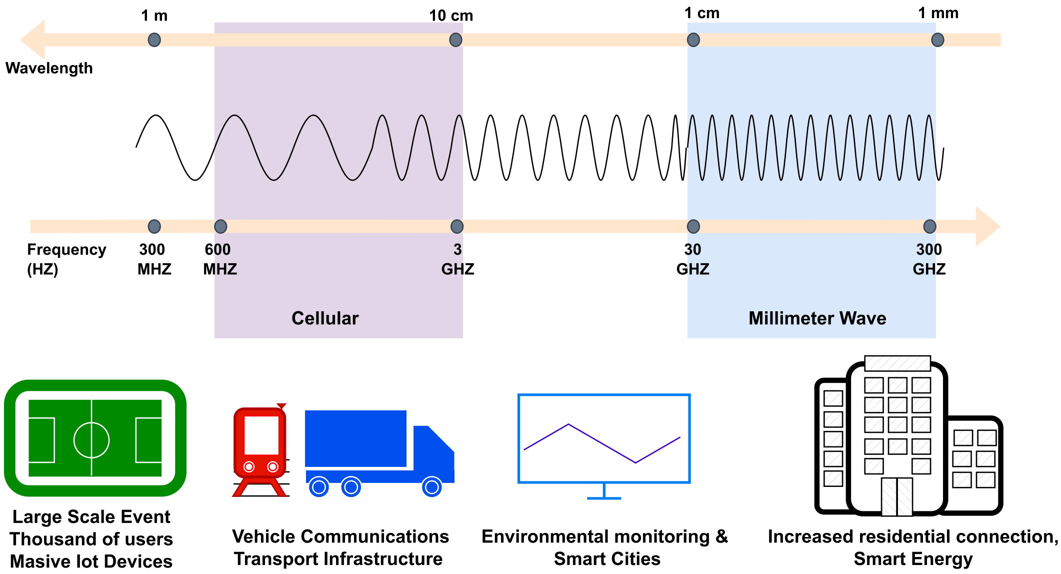

FIGURE 2. mmWave frequency band in communication and smart technologies.

These ultra-high frequencies require novel approaches to antenna design, signal processing, and power management to overcome their inherent limitations in propagation and penetration. To address the massive connectivity demands in this challenging spectral environment, advanced multiple access techniques become crucial. This is where NOMA emerges as a key enabling technology. NOMA's capacity to accommodate multiple users concurrently within the same time-frequency resource block makes it particularly well-suited to handle the dense device ecosystems envisioned for future mmWave and THz networks.

In NOMA technique, channel estimation and signal detection are two tasks that are closely interrelated, each playing a crucial role in system performance [21], [22], [23]. These tasks are not only interrelated but also interdependent, with improvements or optimizations in one area often leading to enhancements in the others. Together, they form a cohesive framework that ensures the efficient and reliable operation of mmWave NOMA-based communication systems.The process of acquiring channel state information (CSI) fundamentally follows a two-step, pilot-based approach. In the first phase, the user equipment (UE) receive a pilot signal from base station (BS) and performs CSI estimation. This involves measuring the received signal's characteristics, such as amplitude, phase, and delay, to estimate the channel's properties. This step is particularly challenging in mmWave systems due to the highly directional nature of transmissions and the need for precise beam alignment. Additionally, in NOMA scenarios, this phase must account for multiple users sharing the same time-frequency resources. In the second phase, the UE sends the estimated CSI back to the BS through the uplink control channel. This feedback is crucial for enabling the BS to adapt its transmission strategies, such as beamforming and power allocation, based on the current channel conditions. Efficient feedback mechanisms are necessary to ensure that the CSI is conveyed accurately and with minimal delay, which is particularly challenging in fast-changing mmWave environments.

Accurate CSI, which describes the wireless channel characteristics between the transmitter (TX) and receiver (RX), is crucial for the effective operation of mmWave NOMA systems. This precise channel knowledge enables BS to perform precoding. Precoding involves computing the optimal signal transmit power for each user, which is particularly important in NOMA to ensure proper power allocation among multiplexed users for successful successive interference cancellation [24].

Signal detection in mmWave-NOMA communication systems plays a vital role in extracting desired signals from noisy environments by utilizing received signals and CSI [25], [26], [27]. In the context of DL based mmWave-NOMA, two main approaches have emerged, data-driven and model-driven detectors. Both approaches leverage the power of deep learning but differ in how they utilize data and models to enhance signal detection performance. Data-driven detectors, which are the focus of the query, directly utilize the received input signal for extraction and classification. These detectors leverage the power of deep learning algorithms to learn complex mappings between received and transmitted signals without relying on explicit mathematical models of the channel or signal propagation. Data-driven detectors, trained on extensive datasets, can potentially handle intricate, non-linear relationships and adapt to changing environments. This approach offers advantages such as the ability to outperform

TABLE 1. The related surveys about DL for resource management in mmwave-NOMA.

Research	Year	Topic	Research Contribution	Limitations
[7]	2020	DL for 5G and beyond communications	Present the use of DL to improve NOMA performance	The paper lacks detailed analysis of DL's role in resource management.
[8]	2021	DL based power allocation schemes in NOMA Systems	Survey power allocation using DL in NOMA system	Lack of investigation DL in power, energy, user, bandwidth and subcarrier allocation
[9]	2021	ML Techniques for 5G and Beyond	Provides a current overview of emerging wireless system concepts like 6G and the role of ML in these future networks.	DL for resource management in mmWave NOMA is not addressed
[10]	2022	DL for Pysical Layer in 5G and beyond	State overview of the key areas of PLS (physical layer security) where DL can be used to enhance the security of wireless networks	DL for mmWave NOMA is not addressed
[11]	2022	ML for 5g and beyond networks	Present the state-of-the-art ML approaches in the context of efficient radio rersource management in 5G/B5G networks.	The paper lacks detailed analysis of DL's role in power, energy, user, bandwidth and subcarrier allocation
[12]	2022	ML-based resource allocation schemes in a Device to Device (D2D) environment	Provide a solution taxonomy for several resource allocation systems that take into account ML, DRL, graph theory, game theory, NOMA, and joint resource allocation.	The paper lacks detailed analysis of DL's role in power, energy, user, bandwidth and subcarrier allocation
[13]	2023	ML for Iot	Explore the influence of ML on the development of next-generation wireless networks.	The paper lacks detailed analysis of DL's role in power, energy, user, bandwidth and subcarrier allocation
[14]	2023	RL for 6G	Conduct a detailed review on RL approaches applied to cross-layer security and privacy protection in the physical layer (PHY) of 6G networks.	DL for Resource management in mmWave NOMA is not addressed
[15]	2023	ML for mmWave and THz bands	Provide an overview of ML algorithm for beam tracking techniques	DL for mmWave NOMA is not addressed
[16]	2024	GAI for physical layer communicatios	Offers a thorough analysis of the applications of GAI in physical layer communications, covering a wide range of conventional problems such as channel estimates, signal classification, and equalization.	DL for mmWave NOMA is not addressed
[17]	2024	ML for UAV NOMA	Review the implement of ML on NOMA for UAV communications	DL for Resource management in mmWave NOMA is not addressed
[18]	2024	AI for Wireless Physical-Layer Technologies (AI4PHY)	The paper provide knowledge about the AI-enhanced designs from the point of view of the basic physical-layer modules, including coding, modulation, multiple access, MIMO, channel estimation, as well as relay transmission	The paper doesn't provide analysis of DL's role in power, energy, user, bandwidth and subcarrier allocation
our paper	2024	A survey of deep learning techniques for resource management in mmWave-NOMA	Describe the functions of DL to optimize resource in mmWave-NOMA network. Resource management consist of • power allocation, energy efficient, user association, bandwidth allocation, subcarrier allocation • Compile the open-source code, dataset, and DL framework • Determines DL for mmWave NOMA patterns and future directions	

traditional methods in scenarios where accurate mathematical models are challenging to derive.

B. RESOURCE MANAGEMENT AND OPTIMIZATION

In wireless communication systems, the central challenges focus on resource management and optimization [28]. Wireless communication systems operate under the constraint of limited resources, including spectrum, time slots, power, and spatial dimensions, which must be carefully managed to maximize system performance. The goal is to enhance metrics such as throughput, coverage, and capacity while addressing the varied QoS needs of modern applications. This involves ensuring adequate data rates for high-speed services, minimizing latency for time-sensitive operations, and maintaining reliability for consistent connections. As the network strives to improve overall performance and efficiency, it must also balance the needs of different users and applications, each with unique requirements. Effective resource allocation strategies become essential, aiming to distribute resources efficiently among users and services, adapt to fluctuating network conditions, and navigate the trade-offs between competing performance metrics. Fair access to resources is crucial, yet it is equally important to prioritize critical services when necessary to maintain system integrity. The complexity of this optimization problem is

TABLE 2. Acronym.

Acronym	Meaning
AI	Artificial Intelligence
AR	Augmented Reality
BCI	Brain-Computer Interfaces
BS	Base Station
CNN	Convolutional Neural Network
CSI	Channel State Information
D2D	Device to Device
DDPG	Deep Deterministic Policy Gradient
DDQN	Double Deep Q-Network
DL	Deep learning
DNN	Deep neural networks
DRL	Deep Reinforcement Learning
DQN	Deep Q-Network
eMBB	Enhanced Mobile Broadband
GAI	Generative AI
IoT	Internet of Things
IRS	Intelligent Reflecting Surface
ML	Machine Learning
MIMO	Multiple Input Multiple Output
m-MIMO-NOMA	Massive MIMO NOMA
mMTC	Massive Machine-Type Communication
mmWave	millimeter wave
NOMA	Non-Orthogonal Multiple Access
QoS	Quality of Service
QL	Q-Learning
RNN	recurrent neural network
RX	Receiver
SE	Spectral Efficiency
SIC	Successive Interference Cancellation
SINR	Signal-to-Interference-Plus-Noise Ratio
SON	Self-Organizing Networks
SSN	Self-Sustaining Networks
STAR-RIS	Simultaneously Transmitting and Reflecting Reconfigurable Intelligent Surface
TX	Transmitter
UE	User Equipment
URLLC	Ultra-Reliable and Low-Latency Communication
VR	Virtual Reality

compounded by the dynamic nature of wireless environments, user interference, and the increasing density of networks. To tackle these challenges, advanced techniques from machine learning, game theory, and convex optimization are employed to develop sophisticated algorithms. Different multiple access schemes introduce distinct resources for allocation. For instance, NOMA incorporates user pairing, grouping, decoding sequence, and power allocation [28].

Decoding sequences play a pivotal role in enhancing spectral efficiency in wireless communication systems, particularly in 5G and beyond. These sequences enable multiple users to simultaneously share the same frequency resources, but also introduce greater complexity in signal processing. The decoding sequence in NOMA directly impacts the success of Successive Interference Cancellation (SIC). In NOMA, multiple users share the same frequency resource but are assigned different power levels. The decoding sequence dictates the order in which the receiver decodes each user's signal. Typically, the signal from the user with the strongest channel gain (often closer to the base station) is decoded first, and its interference is then subtracted from the composite received signal. This process is repeated for the next user, and so on, until the user with the weakest channel gain is decoded [29]. If the decoding order is not optimized, residual interference from stronger users can accumulate, leading to performance degradation, particularly for users with weaker signals. Therefore, the correct decoding sequence is critical issue to minimize interference and enhance spectral efficiency [30].

One critical issue in user association within NOMA systems is the multiplexing of multiple users with varying channel gains within a single resource block (frequency, time, or code) in the power domain. Effective user association is essential for ensuring user fairness and maximizing the overall system capacity. When high-gain users are paired with low-gain users within a cell, mid-gain users are often left to be associated with each other. This can lead to a reduction in system capacity due to the degradation of SIC performance or result in mid-gain users being left unassociated, thereby missing out on the capacity benefits that NOMA can provide. Moreover, the number of users multiplexed within a single resource block presents another challenge in user association. Ideally, a resource block should associate a large number of users to fully exploit the spectrum efficiency benefits of power-domain NOMA (PD-NOMA). However, as the number of users associated with a single resource block exceeds two, the complexity of the system also increases significantly. This complexity arises from the need to manage the interference and power allocation among a larger set of users, which can diminish the efficiency gains if not handled properly.

In scenario of a larger set of users, inter-group or cluster interference occurs between different groups or clusters of users, while Successive SIC typically handles interference within the same group (intra-group). Managing inter-group interference is more challenging, especially in systems with multiple antennas (MIMO), where the order of decoding users is harder to determine compared to single-antenna setups. According to [31] it is explained that multi-antenna systems make it difficult to control inter-group interference because the user channels are more complex. To deal with this, techniques like zero-forcing beamforming are used, but these can be less effective if the signals between groups are too similar. The authors propose a group-based SIC approach that combines power control and signal processing to reduce interference between groups while still using SIC to handle interference within each group. This method improves system performance by efficiently managing both intra- and inter-group interference, resulting in better use of the available bandwidth and lower power consumption compared to older methods. Controlling inter-group interference is key to improving the efficiency of NOMA systems, particularly in setups with multiple antennas and massive users in mmWave frequency.

Power allocation has consistently remained a significant concern across various generations of wireless communication. In NOMA systems, multiple users are multiplexed within a single resource block with different power levels assigned by the transmitter. However, inefficient power allocation schemes can cause considerable interference, system outages due to SIC failures, unfair rate distribution among paired users, and energy inefficiency, all of which contribute to overall performance degradation.Thus, effective power allocation is crucial for improving system performance. In NOMA, power allocation is shaped by factors such as channel conditions, QoS requirements, the availability of CSI, and the total available system power [32], [33], [34].

To address the aforementioned issues in mmWave-NOMA communication networks, the optimal allocation of the following resources is vital: (A) Power allocation (B) Energy efficiency (C) User association (D) Bandwidth allocation (E) Subcarrier allocation

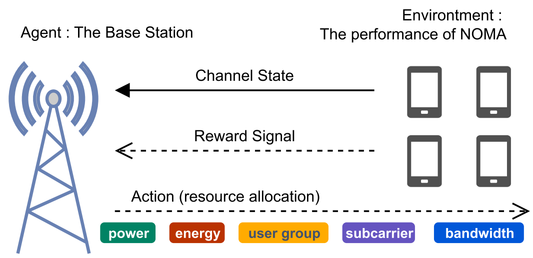

FIGURE 3. Resource assignment using deep learning in mmWave-NOMA.

C. DEEP LEARNING

Game theory and optimization theory are commonly employed in conventional resource allocation techniques. These methods can produce solutions that are Nash equilibrium, mathematically ideal, or suboptimal, but they are frequently quite computationally expensive. With the emergence of 6G wireless networks, there will be a tremendous rise in communication devices and antennas, and data traffic will grow exponentially, will create significant large-scale optimization challenges. Consequently, these traditional algorithms are likely to face even greater computational burdens, making them less feasible for real-time applications. To address this issue, the development of more efficient, scalable algorithms will be crucial for managing the complexity of 6G networks. The integration of advanced techniques, such as machine learning and AI-driven methods, may offer promising alternatives to overcome these challenges and enhance the efficiency of resource allocation in the next-generation networks [28].

The swift progress of AI in recent decades has brought forth a new approach to tackling the complex, non-convex challenges often faced in resource allocation. This innovative approach facilitates the development of resource allocation schemes by learning directly from data samples or environmental inputs, thereby circumventing the need for complex mathematical models traditionally required in this domain. Figure 3 illustrates a non-exhaustive search of potential AI methodologies applicable to resource allocation. These AI-driven methods can be broadly categorized into three main types: traditional machine learning (ML), reinforcement learning (RL), and deep learning (DL). This study offers a concise overview of DL methodologies and examines how these DL-based approaches can be applied to various resource allocation scenarios, as shown in the accompanying Table 7

1) DATA PREPOCESSING

As the multiple access technique is still evolving, comprehensive dataset for research are not abundant. The limited availability of real-world NOMA datasets is a common challenge in emerging technologies. Researchers often need to rely on simulations or create their own datasets through experiments to conduct their studies. There exist datasets such as Didi GAIA [35], DeepMIMO [36], [37] or datasets offered for AI challenges, like the ITU AI/ML in 5G.

As illustrated by Figure 4 regarding the workflow, after data collection, the next step is data preprocessing. This step is a component of a data mining technique that converts raw data into a format optimized for deep learning models. This process aims to make the data more easily parsable and learnable by the model. There are various methods for data transformation, with key techniques including aggregation, dimensionality reduction, sampling, and attribute transformation.

Data quality is paramount in deep learning. Unclean data, which includes duplicates, outliers, missing attributes, or inaccurate information, can significantly degrade the performance and reliability of deep learning models. The preprocessing stage is therefore crucial, as it directly influences the success rate of the model. By cleaning and properly preparing the data, researchers can ensure that their deep learning algorithms are working with high-quality, relevant information. This not only improves the model's accuracy and generalization capabilities but also enhances the interpretability and reliability of the results. Ultimately, the effort invested in thorough data preprocessing pays off in the form of more robust, accurate, and trustworthy deep learning models for activity resource management in mmWave-NOMA.

2) DL MODELS

DL-based NOMA have significantly advanced and found applications in various scenarios. In wireless communication networks, particularly 5G and beyond, NOMA improves spectral efficiency and user connectivity, with DL enhancing resource allocation and managing interference. DL as a subset of ML can be classified into three broad categories: DRL, supervised learning, and unsupervised learning [38]. Each of these categories has unique characteristics and applications that make them suitable for different types of tasks. RL entails an agent learning to make decisions through interactions with its environment and receiving rewards or penalties based on its actions, making it useful for tasks like robotics, autonomous driving, and game playing. Supervised Learning entails training a model on labeled datasets to map inputs to outputs, commonly utilized in image classification, speech recognition, and natural language processing. Unsupervised Learning deals with unlabeled data, identifying patterns and structures without explicit guidance, and is applicable in clustering, dimensionality reduction, and anomaly detection, useful for exploratory data analysis and scenarios where labeling is impractical. These categories provide a comprehensive framework for addressing complex problems in various domains, optimizing deep learning-based NOMA

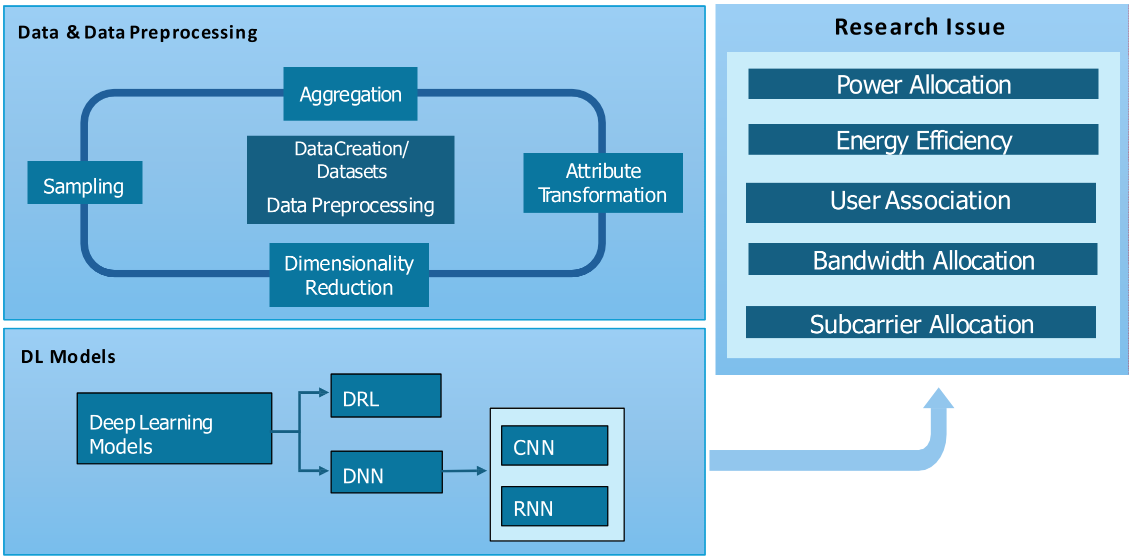

FIGURE 4. Overview of data preprocessing and DL models for research challenges.

systems to manage the growing complexity and data demands of modern communication networks.

As 5G and beyond communications continue to evolve, deep learning emerges as a highly effective tool for addressing various challenges, including LDPC coding for encoding and decoding, power control in massive MIMO systems, power-based and code-based NOMA, resource allocation, and security. The most commonly employed models in 5G/6G research include DRL, DNN, CNN, and RNN [38]. These models offer advanced capabilities in handling the complex and dynamic requirements of 5G networks. DRL can optimize resource allocation and power control by learning efficient policies through interactions with the network environment. DNNs are utilized for their ability to model intricate relationships and predict network behaviors accurately. CNNs excel in processing and analyzing large volumes of data, making them ideal for tasks such as signal detection and channel estimation. LSTMs, with their proficiency in handling sequential data, are effective in managing time-series predictions and understanding temporal dependencies in network traffic. By leveraging these deep learning models, 5G networks can achieve enhanced performance, reliability, and security, addressing the diverse and demanding needs of modern communication systems.

- DRL
  DRL is built upon the principle of learning through interaction. Unlike traditional learning methods where specific actions are prescribed, RF enables an agent to discover which actions yield the highest rewards through trial and error. This paradigm consists of two primary components: the agent and the environment. The agent engages with the surroundings, making choices and getting input in the form of incentives or sanctions, guiding its learning process. DRL extends RL's capabilities by integrating DNNs into the framework, enhancing the agent's ability to learn and make decisions. The incorporation of DNNs allows the agent to replace traditional tabular strategies for function approximation methods estimation of state values, enabling generalization to previously unencountered states. This self-sufficiency enables DRL agents to independently learn and adapt to new situations through their interactions with the environment, eliminating the need for predefined action rules [38].
  In the context of wireless communication, DRL frameworks offer a promising solution to efficiently manage resources, adapt to varying network conditions, and optimize overall system performance, especially as networks continue to grow in scale and complexity. Abiko et al. [39] and Yu et al. [40] implemented a network slicing architecture based on DRL to satisfy various QoS needs in 5G networks. Their approach prioritizes efficient resource allocation to reduce energy usage of remote radio heads (RRHs).
  In this paper, we explore how DL techniques, particularly DRL, can optimize resource allocation in mmWave-NOMA systems. DRL has emerged as a powerful tool in addressing the dynamic and complex nature of wireless networks, enabling efficient decision-making based on environmental observations without requiring labeled data. This makes DRL particularly well-suited for mmWave communications, where channel conditions can vary rapidly due to user mobility and obstacles.
  Recent advancements, such as the work by Xu et al. [41], have further demonstrated the effectiveness of DRL in mmWave communications. In their study, a location-aware imitation environment is used to train a DRL

model for joint beamforming in reconfigurable intelligent surface (RIS)-aided mmWave MIMO systems. By leveraging user location information, the proposed DRL algorithm efficiently manages beamforming without relying on precise channel state information (CSI), which is often difficult to obtain in real-world scenarios. This approach aligns with our focus on optimizing resource allocation in mmWave-NOMA systems. The location-aware strategy and use of imitation environments can be extended to enhance resource allocation mechanisms, such as power, bandwidth, and user association, in fast-varying mmWave environments. By incorporating DRL-based methods, we aim to improve spectral and energy efficiency while maintaining system scalability under dynamic conditions.

- DNN
  Artificial neural network (ANN) serve as the foundational framework for various deep learning models. These networks can range from shallow architectures, which contain only a single hidden layer, to deep architectures, known as DNN, which incorporate multiple hidden layers. DNN, in particular, have garnered widespread acclaim and adoption in research due to their remarkable performance on benchmark problems and their applicability across a wide array of tasks. The most basic form of an ANN is the feed-forward neural network (FNN), where data flows in a single direction from input to output. When an FNN comprises more than one hidden layer, it evolves into a deep feed-forward neural network (DFF), enhancing its capacity to model complex relationships within the data [38]. Among the various types of DNNs, CNNs and RNNs stand out due to their specialized structures and functionalities. CNNs are particularly adept at handling image and spatial data, making them indispensable for tasks such as image recognition, object detection, and computer vision applications. The unique capabilities of these advanced DNNs enable them to tackle complex problems that were previously beyond the reach of traditional machine learning methods, thereby pushing the boundaries of what can be achieved in fields such as wireless communication, healthcare, finance, and more.
- CNN
  CNNs are a widely utilized deep learning algorithm, particularly effective for image recognition tasks. Their ability to automatically detect and learn spatial hierarchies of features from raw pixel data makes them indispensable in fields requiring high accuracy in visual data processing, such as computer vision and autonomous systems [42], [43]. However, CNNs are not restricted to image data; they can also be applied to other types of data, such as analyzing the characteristics of NOMA users. This adaptability makes CNNs valuable in various domains, enabling them to uncover patterns and relationships in different types of complex data, which is particularly useful in optimizing network performance and resource management in communication systems. CNNs have the ability to extract features from NOMA user data, such as channel conditions, user locations, and power levels, which can be used to train models for power allocation. This feature allows CNNs to enhance power allocation in NOMA systems by efficiently analyzing and processing user-specific data. By leveraging this capability, CNNs contribute to more precise and adaptive resource management, ultimately improving the overall performance and fairness in NOMA networks [44].
- RNN
  RNNs differ significantly from CNNs in their structure and application. While CNNs are designed to handle spatial data and are extensively used for image recognition tasks, RNNs are specifically tailored to process sequential data. This makes RNNs particularly effective for tasks involving text and speech analysis, where the order and context of the data are crucial for accurate understanding and prediction [38]. One disadvantage of RNNs is that they suffer from gradient vanishing and exploding problems, which can hinder their ability to learn long-term dependencies. To address this issue, Long Short-Term Memory (LSTM) networks were introduced. LSTMs are specialized in processing and predicting time series with time lags of unknown duration, using three types of gates: the input gate, the forget gate, and the output gate. These gates help regulate the flow of information, allowing LSTMs to maintain and update the cell state over long sequences, thus effectively capturing long-term dependencies and improving performance in tasks involving sequential data.
  In 5G and beyond, LSTM networks have a diverse range of applications. They are employed in the study of MIMO systems, where they help model and predict complex spatial-temporal channel characteristics. LSTMs are also used in multiple access schemes to efficiently manage and predict user traffic patterns. Furthermore, they play a crucial role in resource allocation by forecasting demand and optimizing the distribution of resources. In terms of security, LSTMs are utilized to detect and predict anomalies or potential threats, thereby enhancing the robustness and reliability of 5G networks [38].
  Yu et al. and Gui et al. integrated LSTM networks into frameworks for resource allocation and multiple access, with a specific focus on NOMA. In these applications, LSTMs were employed to generate highly accurate predictions, which were then compared against the performance of other recent methods. The researchers used traffic data from a self-organizing network (SON) entity to enhance the accuracy of the LSTM model. These precise predictions were subsequently utilized

to develop a DRL framework aimed at efficiently allocating wireless resources for energy-efficient TV broadcast services. This approach demonstrated the effectiveness of LSTMs in enhancing both the precision and efficiency of resource allocation in modern wireless networks. The successful application of LSTM in this context underscores its potential to drive advancements in next-generation communication systems, particularly in scenarios requiring high accuracy and adaptive resource management [40].

D. DATASET, SOURCE CODE, AND DL FRAMEWORK

With the advancement of deep learning, a growing body of research has emerged addressing problems in communication fields utilizing deep learning techniques. However, reproducible research remains challenging, as most communication-related papers do not provide open source code. In recent years, the number of communication papers leveraging deep learning has risen sharpely, and their authors have shown a greater inclination to share their code openly. To further advance DL-based resource management in mmWave NOMA, we present a collection of open-source DL frameworks, presented in Table 3, are tools designed to help researchers develop, prototype, and deploy DL models in production, supporting existing DL algorithms and allowing for quick experimentation. To further facilitate the development of DL-based mmWave-NOMA, we provide a list of relevant data sets in Table 4. Additionally, Table 5 provides a summary of recent research on power allocation, energy efficiency, and subcarrier allocation accompanied by their open source code. However, due to limitations, only open-source codes for these three areas were found, while others like user association and bandwidth allocation might not have been covered.

In science, sharing is the way to enable research reproducibility and swift improvements of the state-of-the-art. The availability of these resources including DL frameworks, datasets, and open source code, is anticipated to significantly accelerate research progress in the field of DL for mmWave NOMA.

E. EVOLUTION OF NOMA IN 3GPP RELEASES

The development of NOMA has played a significant role in enhancing spectral efficiency and connectivity within wireless networks. NOMA was first introduced in 3GPP Release 13 under the framework of multiuser superposition transmission (MUST), specifically for LTE downlink and uplink scenarios [58]. In 3GPP Release 14,MUST was further enhanced [58]. Release 14 introduced refinements to MUST as part of the ongoing efforts to improve the performance of NOMA techniques. The enhancements in Release 14 primarily focused on optimizing system performance in scenarios involving multiple users with different channel conditions, improving spectral efficiency, and addressing practical implementation issues like interference management and decoding complexity. The technique allowed multiple users to share the same time-frequency resources by assigning different power levels, thereby improving spectral efficiency. In Release 15, NOMA was explored as a potential candidate for 5G New Radio (NR), but it was not standardized at this stage, with the release focusing on establishing core 5G NR standards while leaving room for future evaluations of NOMA's role.

In Release 16, a comprehensive study was conducted on PD-NOMA for 5G NR [59]. This investigation primarily examined NOMA's potential to enhance system performance, particularly in the context of massive machine-type communications (mMTC) and ultra-reliable low-latency communication (URLLC). However, the study revealed that the practical gains from NOMA, especially when compared to other advanced techniques such as multi-user MIMO and beamforming, were relatively modest. As a result, Release 17 marked the exclusion of NOMA from further standardization [60]. The complexity of managing SIC in NOMA, combined with its limited performance improvements in real-world 5G deployments, led to this decision. The industry concluded that other technologies offered more scalable and efficient solutions for 5G networks.

In subsequent releases, Release 18 and Release 19, NOMA remained excluded from 3GPP's working groups as the focus shifted toward more promising technologies such as AI/ML-based resource management, massive MIMO, and full-duplex communication. These emerging techniques have been prioritized to meet the increasing demands of Beyond 5G (B5G) and 6G networks, where efficiency, scalability, and real-time adaptability are crucial.

However, despite its exclusion from the 3GPP standards beyond Release 17, NOMA continues to attract significant attention from the research community. Researchers are actively exploring its potential applications in 6G networks, where extreme connectivity, low-latency communications, and energy efficiency are critical. Academic studies are investigating how NOMA can be integrated with AI/ML for dynamic resource allocation and interference management, particularly in massive machine-type communications and IoT scenarios. These ongoing research efforts indicate that while NOMA's role in 5G standardization may have diminished, its potential for future network generations remains a vibrant area of exploration.

A summary table detailing the development of NOMA in 3GPP standards, including the specific releases where NOMA was excluded from further work, as illustrated in Table 6

III. DL FOR RESOURCE MANAGEMENT

A. SYSTEM MODEL

Figure 5 presents the proposed system model for efficient resource management in mmWave-NOMA systems, utilizing DL to optimize key allocation tasks. The model addresses the massive connectivity and the increasing demand for high-capacity, high-speed applications such as augmented

TABLE 3. Open source framework.

DL Framework	Key Features
HyDNN [45]	• Hybrid Model: Combines deep learning with traditional methods for channel estimation and signal detection. • Multiuser Uplink Channel Estimation: Focuses on efficient channel estimation for multiple users in an uplink scenario. • Improved Signal Detection: Enhances signal detection accuracy using deep neural networks. • Interference Management: Addresses the interference challenges inherent in NOMA systems.
UAV-NOMA [46]	The UAV NOMA framework is a comprehensive tool for studying the influence of different parameters on UAV performance-enabled NOMA systems, focusing on aspects like outage probability and achievable rates under different conditions
SIONNA [47] [48]	An open-source library built on TensorFlow for simulating the physical layer of wireless and optical communication systems.
DeepNOMA [49]	• Unified Multi-Task Learning: DeepNOMA uses a deep learning approach to handle multiple overlapping transmissions as related tasks, improving overall optimization. • Key Modules: DeepMAS: This module generates multiple access signatures and handles different modulation schemes. It simplifies implementation by using predefined symbol shapes. DeepMUD: This module detects and separates the superimposed signals to recover the original messages accurately. It includes an Interference Cancellation-enabled DNN to enhance detection and reduce complexity. • Versatility: DeepNOMA works well across various channel models, including both AWGN and fading channels, proving its effectiveness in different conditions.
NOMA Simulator [50]	A simulator tools that supports both single and multi-carrier systems, including different forms of SIC. It allows for comprehensive performance evaluation using metrics like bit error rate (BER) and throughput, and considers multi-cell scenarios with intercell interference. Additionally, it is designed for reproducible research and includes features like adaptive modulation and coding, resource allocation strategies, and various channel models.

TABLE 4. Open source dataset.

Dataset Name	Description	Data Modalities	Related Resarch	Link
Didi GAIA	A dataset framework includes tools for data handling, trajectory plotting, and creating heatmaps using Python scripts and Jupyter Notebooks.	GPS Trajectory Data, CSV Files, Heatmaps and Trajectory Plots	[35]	https://github.com/neardws/Vehicular-Trajectories-Processing-for-Didi-Open-Data
DeepMIMO	Provides large-scale 3D ray-tracing datasets for millimeter-wave and massive MIMO systems, supporting 5G NR channel models. It includes tools for simulation setup and dataset generation, compatible with MATLAB, Octave, and Python.	Ray-Tracing scenarios, customizable parameters, channel data, user location and movement	[36] [37]	https://www.deepmimo.net/
NOMA AMC MR-CNN	The repository is designed to assist with research in modulation classification within NOMA systems using deep learning techniques, particularly Modified Residual-CNN.	Signal types, channels, or features extracted from communication signals.	[51]	https://github.com/ashokparmar29/NOMA_AMC_MRCNN

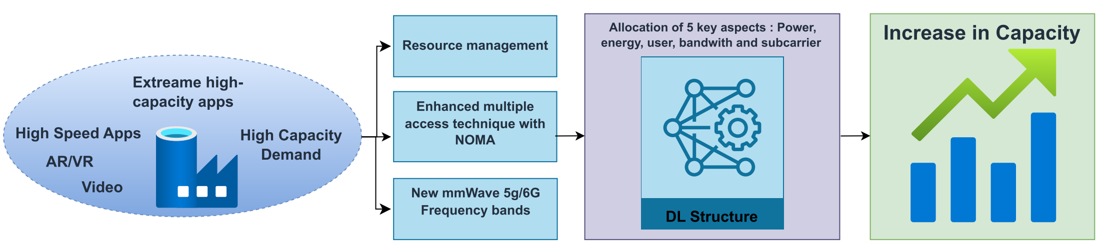

FIGURE 5. System model.

reality (AR), virtual reality (VR), and high-definition video streaming, which are driving the need for advanced wireless communication techniques.

The leftmost part of the figure shows the extreme capacity demand generated by high-speed applications, necessitating robust and scalable resource management strategies.

TABLE 5. Research with open-source code related.

Category	Research	DL Type	Code
Power Allocation	[35]	DRL, DDPG	https://github.com/neardws/Game-Theoretic-Deep-Reinforcement-Learning
Power Allocation	[52]	DRL	https://github.com/sinannasir/Spectrum-Power-Allocation
Power Allocation	[53]	ANN	https://github.com/3seoksw/Downlink-NOMA-with-RL
Power Allocation	[54]	DNN	https://github.com/wjddn279/DeepLearning_MIMO-NOMA
Power Allocation	[55]	DQN	https://github.com/Frost-Armor/Multi-Agent-Reinforcement-Learning-in-NOMA-Aided-UAV-Networks-for-Cellular-Offloading
energy efficiency	[56]	DDPG	https://github.com/zhiguo-ding/CRNOMA_DDPG
Subcarrier Allocation	[57]	Q-Learning	https://github.com/tomdiudiu/QLearning_NOMA_PowerControl
User Association			Not Available
Bandwidth Allocation			Not Available

This demand is met by the integration of enhanced multiple access techniques through NOMA, which is particularly effective in mmWave communications. NOMA enables the simultaneous transmission to multiple users over the same frequency band by exploiting differences in user channel conditions, thereby improving spectral efficiency.

At the core of the model, DL is employed to handle the complexity of allocating five key resources: power, energy, user, bandwidth, and subcarrier. The DL structure leverages real-time data to dynamically optimize these resources, adapting to the rapidly changing network environment typical of mmWave bands. By managing these critical aspects efficiently, DL enhances the system's ability to allocate resources based on user demand, network conditions, and application requirements.

The rightmost part of the figure illustrates the outcome of the proposed system model, an increase in network capacity. Through the combined use of DL and NOMA, the system not only meets high-capacity demands but also maximizes the use of available spectrum, ensuring scalability and efficiency for next-generation wireless networks, including 5G and beyond.

B. DL FOR POWER ALLOCATION IN mmWave-NOMA

The transmit power in wireless communication is the amount of electrical energy a transmitter uses to send a signal. In mmWave-NOMA networks, effective and reliable data transmission among users is critically dependent on power allocation. This process involves dividing, distributing, and assigning the total available power to specific users within the network [61]. Furthermore, to establish connections and facilitate data sharing, it is crucial to allocate power resources among various UE entities. Managing transmission power is vital for preserving signal quality, mitigating interference, and optimizing energy usage, particularly in battery-dependent devices such as IoT gadgets, smartphones, and vehicles in V2X scenarios. However, achieving efficient power allocation presents significant challenges, including the dynamic nature of UE environments, the complexity of multipath propagation in V2X communications, varying IoT requirements, and the risk of interference from excessive power transmission among neighboring users. Addressing these challenges is key to improving network performance and energy efficiency.

Unlike traditional OMA schemes, where each resource block (such as time, frequency, or subcarriers) is allocated to a single user, in this approach, a group of M users is overlaid on the same resource block simultaneously. At the transmitter side, the data for these M users is combined by superposing them on top of each other with varying power levels over the same resource block, as illustrated in Figure 6. TThe amount of distance between a user and the base station (BS) determines the fading and path loss of the signal that is broadcast to each user. The complex channel coefficient h_m between UE-m and the BS is expressed as

$$h_m = \frac{g_m}{\sqrt{1 + d_m^\alpha}}$$

where g_m represents the Rayleigh fading channel gain, α is the path loss exponent, and d_m denotes the distance between user m and the BS. Given two users, UE-M is the farthest user (FU) and UE-1 is the closest (NU). Power distribution in PD-NOMA is inversely correlated with the channel coefficient h_m. This suggests that UE-M receives

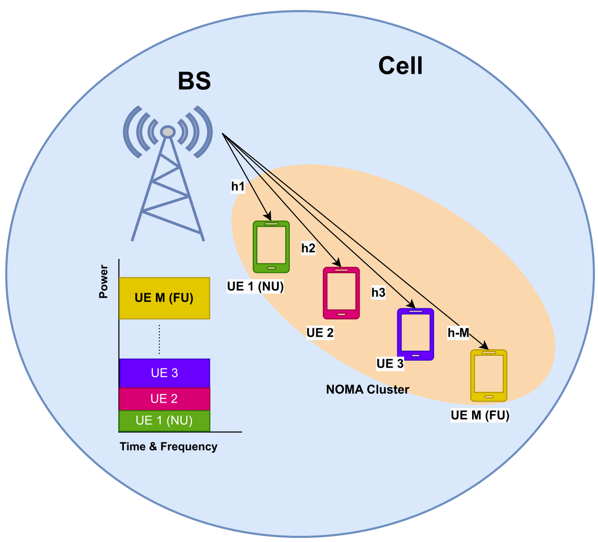

FIGURE 6. Power allocation in mmWave-NOMA cluster.

TABLE 6. The development of NOMA in 3GPP standards.

3GPP Release	Study/Report	Key Features	NOMA Status	References
Release 13, 14	Multiuser Superposition Transmission (MUST)	• First introduction of NOMA in LTE. • Downlink (DL) and uplink (UL) MUST for LTE spectral efficiency.	NOMA introduced for LTE in downlink and uplink scenarios	3GPP TR 36.859 V14.0.0 (2016)
Release 15	5G New Radio (NR) Initial Standardization	• Focus on establishing 5G NR. • NOMA explored but not yet standardized for NR.	NOMA studied as a potential technique but not finalized in 5G NR.	3GPP TR 38.812 V15.0.0 (2018)
Release 16	Study on Non-Orthogonal Multiple Access for NR	• Detailed investigation of NOMA for 5G NR. • Focus on Power-Domain NOMA (PD-NOMA) for mMTC and URLLC.	NOMA studied for NR but findings show limited practical gains.	3GPP.38.812.V1600
3GPP has split the 5G standard into two releases: Release 15, which corresponds to NR Phase 1, and Release 16, which corresponds to NR Phase 2				
Release 17	Further Enhancements for 5G NR	• Focus on advanced technologies like massive MIMO and beamforming. • No further work on NOMA.	NOMA officially excluded from further work in 5G NR due to limited performance gains in real-world scenarios.	
Release 18	5G-Advanced for B5G/6G	• Focus on AI/ML-based resource management, massive MIMO, and full-duplex communication.	NOMA excluded from Release 18; focus shifted to more advanced techniques like AI-driven resource allocation.	
Release 19	Further Enhancements for 6G	• Focus on Terahertz (THz) communication, AI-driven networks, and advanced MIMO.	NOMA excluded from Release 19; other resource management and communication techniques prioritized.	Release 19 Studies and Planning

the greatest share of the transmitted power, whereas UE-1 receives the least amount.

The channel gains of all users are sorted in descending order as follows: $|h_1|^2 > |h_2|^2 > |h_3|^2 > \cdots > |h_m|^2 > \cdots > |h_M|^2$. Consequently, the power allocation ratios α_m follow the order $\alpha_1 < \alpha_2 < \alpha_3 < \cdots < \alpha_m < \cdots < \alpha_M$, with the condition $\sum_{m=1}^{M} \alpha_m = 1$ [62].

A growing number of researchers have turned their attention to this complex nature of power allocation in mmWave-NOMA systems as shown in Table 7. Tharani et al. in [63] employed a Recurrent Neural Network (RNN) to enhance power allocation in hybrid TDMA-NOMA systems, addressing the limitations posed by imperfect channel state information (CSI). Their model demonstrated significant improvements in resource efficiency by mitigating the outage probability caused by inaccurate CSI. In contrast, Sobhi-Givi et al. in [64] proposed a Deep Deterministic Policy Gradient (DDPG) algorithm to jointly optimize power allocation and user fairness in mmWave-NOMA heterogeneous networks, with a particular focus on managing imperfect successive interference cancellation (SIC). Their reinforcement learning-based approach not only minimized transmission power but also enhanced user fairness, making it highly effective for practical deployments with real-world hardware limitations.

Pramitarini et al. in [65] introduced an Opportunistic Scheduling Scheme to improve physical-layer security in cooperative NOMA systems, addressing the critical issue of passive eavesdropping. By leveraging a deep neural network (DNN) for real-time optimization, they were able to predict channel capacities and optimize power allocation, significantly reducing secrecy outage probability. Their approach outperformed conventional scheduling schemes in both secrecy performance and computational efficiency, demonstrating the potential of DL to enhance security in high-stakes communication environments.

Zhenyu et al. in [66] advanced this field with a Two-way DRL framework that combined Double Deep Q Networks (DDQN) and DDPG to solve the complex resource allocation problem in cognitive network slicing for Power Domain Sparse Code Multiple Access (PD-SCMA) systems. Their dual-layered approach allowed for the simultaneous optimization of discrete codebook assignments and continuous power allocation, resulting in superior spectral efficiency and improved QoS compared to traditional algorithms. Similarly, Yoga Perdana et al. in [67] proposed a DL-based framework for spectral efficiency maximization in massive MIMO-NOMA systems with STAR-RIS. Their solution, which jointly optimized user power allocation and the phase shift matrix of transmission and reflection elements, demonstrated notable gains in spectral efficiency over conventional methods, particularly in scenarios involving cell-edge users and obstacles.

Finally, Albelaihi et al. [68] developed a DRL approach for client selection in NOMA-based federated learning (FL) systems. Their DREAM-FL algorithm dynamically optimized client selection and power allocation, significantly enhancing bandwidth utilization and increasing the number of selected clients compared to conventional FDMA and TDMA-based methods. By integrating DRL, they demonstrated the potential for more efficient and scalable client selection in IoT environments where real-time adaptation is crucial.

These diverse approaches underscore the versatility of deep learning in addressing key challenges in NOMA systems, ranging from spectral efficiency and power management to physical-layer security and user fairness. Together, they reveal the transformative potential of DL techniques in modern wireless communication networks.

C. DL FOR ENERGY EFFICIENCY IN mmWave-NOMA

The escalating number of users in the mmWave frequency band, along with the emergence of advanced applications in 5G and future 6G networks, necessitates energy-efficient allocation methods to meet the growing demand while ensuring the sustainability of network operations. Efficient energy usage at the site level requires flexible resource management and operational oversight. Cost considerations will play a key role in processes, assembly, distribution efficiency, and energy consumption metrics [69].

In a downlink NOMA system, energy consumption is closely related to the transmission power and the SINR for both near and far users [70], where energy efficiency is critical due to the complexity of allocating resources for near and far users under SINR constraints, deep learning can offer substantial advantages in improving energy efficiency.

Refering to Table 7 researchers have investigated the application of DL to energy efficiency in mmWave NOMA. Studies like Guo et al. in [71] proposed a DRL approach combined with Monte Carlo Tree Search (MCTS) for resource assignment in cooperative NOMA-enhanced cellular networks. The problem was formulated as a two-step optimization: deriving closed-form power control expressions and then solving the joint user pairing and subchannel assignment problem via MCTS. Their results demonstrated that this approach outperforms conventional schemes in terms of energy efficiency with negligible computational time, particularly in cooperative decode-and-forward (DF) scenarios, where users with better channel conditions relay signals for weaker users.

In contrast, Perdana et al. in [72] focused on maximizing energy efficiency in massive MIMO-NOMA networks with multiple RISs. They tackled a non-convex optimization problem by decoupling it into phase shift and beamforming sub-problems. A bisection search algorithm and an iterative inner approximation (IA) method were employed to solve these sub-problems. Their DL-based framework predicted optimal solutions for the phase shifts of RISs and precoding matrices in real-time, achieving a high accuracy and significant reductions in execution time. The simulation results showed marked improvements in energy efficiency, especially with increasing RIS elements and antenna arrays at the BS.

Both studies addressed energy efficiency but through different mechanisms: Guo et al. employed DRL and MCTS to optimize user pairing and resource assignment, enhancing system flexibility in dynamic environments, while Perdana et al. used a DL-based optimization framework tailored for large-scale MIMO-NOMA networks, focusing on phase shift and beamforming adjustments. These complementary methodologies highlight the versatility of DL in solving energy efficiency challenges in NOMA systems, with Guo et al. excelling in cooperative NOMA setups and Perdana et al. providing an efficient solution for networks with RIS-aided MIMO configurations.

D. DL FOR USER ASSOCIATION IN mmWave-NOMA

User association refers to the process of figuring out which users should be grouped, paired, or clustered together for simultaneous transmission while considering the unique challenges of mmWave frequencies.

A number of issues, including as channel fluctuations, different QoS requirements, user mobility, network heterogeneity, and the necessity for energy efficiency, emerge when user density in wireless networks rises. These challenges are further compounded by the dynamic nature of channel conditions and the fluctuating number of users within a cell, each with distinct QoS demands. To effectively address these issues and enhance network energy efficiency, the implementation of adaptive user clustering is needed properly. The network creates clusters before implementing NOMA within these clusters [73].

This clustering can be approached from various perspectives, each aiming to optimize different facets of the system.

For example, users may be grouped based on their CSI, such as channel gain or correlation, to improve power allocation and reduce interference. Another perspective considers the QoS requirements, where users with similar data rate or latency demands are clustered together, ensuring consistent service delivery across the network. For instance, Hurianti Vidyaningtyas in [74] emphasized the importance of clustering based on channel conditions by utilized supervised machine learning classification algorithm, which can enhance overall sum-rate and fairness among users.

The optimization of user association in mmWave-NOMA systems has been approached with various DL methods across different research studies, each focusing on unique aspects of performance improvement. Wang et al. in [75] proposed a Dueling Deep Q-Network (DQN) and Deep Deterministic Policy Gradient (DDPG) framework for user grouping and resource allocation in mmWave massive MIMO-NOMA systems. Their approach, enhanced by K-means clustering, improves spectral efficiency and accelerates convergence. The results showed superior system capacity and reduced power quantization errors compared to traditional methods like random scheduling and DoubleDQN. Similarly, Li et al. in [76] used a DL-based power allocation algorithm for NOMA downlink systems, achieving a 19% improvement in system sum rate by employing a step-by-step user grouping method that prevents users with similar channel gains from being paired together, thereby reducing interference.

Liu et al. in [77] extended this concept by introducing a Prioritized Dueling DQN-DDPG network to address slow convergence and unstable training in traditional DQN models. Their method incorporates priority sampling based on TD-error (Temporal-difference error), improving both convergence speed and training efficiency. This approach demonstrated significant performance gains in system throughput over conventional reinforcement learning algorithms. In contrast, Vishnoi et al. in [78] tackled the problem of co-channel and cross-channel interference in Device-to-Device (D2D) communication using a distributed DDPG-based framework. Their solution maximized sum rate and fairness among NOMA-enabled cellular users (CUs) and D2D pairs, achieving a 49.8% higher sum rate compared to other DRL-based methods.

Cong et al. in [79] addressed user clustering and power allocation in vehicular networks, proposing a Proximal Policy Optimization (PPO) algorithm. Their method reduced system latency by 8.4% compared to benchmark algorithms while optimizing power allocation and task scheduling for multi-user multi-server networks. Kim et al. in [80] utilized a DNN-based user selection and power allocation technique for downlink MISO-NOMA systems, using SINR instead of channel state information (CSI). Their model significantly reduced computational complexity while maintaining comparable performance to optimal solutions. Lastly, Zou et al. in [81] designed a Machine Learning (ML)-based user scheduling and beam selection framework for millimeter-wave systems, employing the Whale Optimization Algorithm (WOA) to achieve a near-global-optimal solution. Their method provided a balance between fast convergence and system performance improvement, offering practical advantages in real-time applications.

Each of these studies demonstrated the flexibility and effectiveness of DL techniques in addressing user association and power allocation challenges in NOMA systems. While some focused on improving spectral efficiency and sum rate, others targeted reducing latency, maximizing fairness, or handling complex interference scenarios, showcasing the versatility of deep learning in solving diverse problems in wireless communication networks.

E. DL FOR BANDWIDTH ALLOCATION IN mmWave-NOMA

Optimizing bandwidth allocation is essential for achieving high spectral efficiency and minimizing latency. DL techniques can learn optimal allocation strategies from historical data and adapt to changing network conditions.

Hu et al. in [82] and Li et al. [83] both present deep learning-based solutions to optimize bandwidth allocation in NOMA systems, but with distinct focuses and methodologies. Hu et al. tackled the challenge of resource allocation in terahertz (THz) NOMA systems, proposing a multi-task deep reinforcement learning (DRL) framework called DISCO to handle the hybrid discrete and continuous nature of power, sub-band, and sub-array allocations. The problem of beamforming-bandwidth-power (BBP) allocation is formulated as a non-deterministic polynomial-time hard (NP-hard) problem. The authors designed their model to maximize long-term throughput while addressing fairness and minimizing computational complexity. Their results demonstrated that DISCO outperforms conventional greedy algorithms and other DRL methods, improving throughput by 49% with minimal computational overhead, highlighting its practical applicability to real-time systems.

Li et al., on the other hand, focused on bandwidth and power optimization in multi-carrier NOMA (MC-NOMA)-empowered wireless federated learning (WFL) systems. Their approach involved maximizing the Weighted Global Proportion of Trained Mini-batches (WGPTM), a new metric designed to measure system convergence speed, by jointly optimizing the power and bandwidth allocations in a non-convex problem. The problem was solved using variable substitution and Cauchy's inequality, allowing Li et al. to transform the non-convex problem into a convex one. Simulation results demonstrated that their approach reduced communication delays and increased the number of training iterations, speeding up system convergence by over 40% compared to MC-OMA WFL systems.

While both papers used deep learning to optimize resource allocation, Hu et al. focused on balancing throughput and fairness in a high-frequency THz-NOMA environment, whereas Li et al. concentrated on improving convergence speed and system efficiency in MC-NOMA WFL systems. Together, these studies illustrate the versatility of deep learning in addressing complex bandwidth allocation problems in NOMA systems, showing that both long-term system throughput and real-time learning convergence can be significantly enhanced through tailored deep learning algorithms.

F. DL FOR SUBCARRIER ALLOCATION IN mmWave-NOMA

In recent studies, various DL methodologies have been proposed to optimize subcarrier allocation in mmWave NOMA systems, each addressing specific challenges. Alajmi and Ghandoura in [84] presented a multi-agent Deep Q-Network (DQN) framework to handle the resource allocation problem in grant-free (GF) NOMA systems, taking into account imperfections in SIC. Their approach allows unrestricted user subcarrier selection, leading to a 62.1% improvement in user fairness and higher spectral efficiency compared to benchmark schemes. Zhang et al. in [85] employed a DQN-based hybrid spectrum access strategy in cognitive radio NOMA networks, focusing on maximizing spectral efficiency while satisfying Quality of Service (QoS) requirements. Their results showed faster convergence and higher spectral efficiency compared to Q-Learning and other hybrid access models, making it suitable for complex cognitive network environments.

Liu et al. in [86] used a DRL framework that combines DQN for subcarrier allocation and DDPG for power allocation. The focus was on satisfying the diverse demands of real-time (RT) and best-effort (BE) users in mixed-traffic NOMA systems. Their solution significantly outperformed conventional methods by optimizing both throughput and fairness while managing the subcarrier assignments under varying traffic conditions. Finally, Park et al. in [87] proposed a two-step optimization using a genetic algorithm (GA) for sub-band assignment and unsupervised learning (USL) via deep neural networks (DNN) for power allocation in uplink IoT NOMA networks. Their approach minimized transmit power while maintaining required data rates for IoT devices, achieving near-optimal results with reduced computational complexity.

Each of these studies contributes to the optimization of subcarrier allocation in NOMA systems, with Alajmi and Ghandoura focusing on grant-free NOMA efficiency under SIC imperfections, Zhang et al. addressing cognitive network complexities, Liu et al. balancing mixed traffic demands, and Park et al. achieving power minimization in IoT environments. Together, they demonstrate the versatility and effectiveness of DL techniques in solving dynamic and non-convex resource allocation problems in mmWave NOMA systems.

Nevertheless, deep learning is increasingly employed to address multiple challenges simultaneously, particularly in joint optimization tasks within mmWave-NOMA systems, such as user grouping, pairing, and power allocation. Traditionally, these joint optimization problems are handled using iterative, decoupled sequential optimization methods, where each component (e.g., user grouping or power allocation) is solved independently [88], [89]. This approach often leads to suboptimal results, as the interdependencies between components are not fully captured. However, deep learning offers a more integrated approach by enabling simultaneous optimization of all variables. This not only reduces the overall complexity and computational time but also improves system performance in NOMA networks through the following key aspects:

- **Deep Learning and Joint Optimization**
  Deep learning techniques, particularly Deep Reinforcement Learning (DRL), can optimize multiple resource allocation tasks concurrently. By learning directly from network conditions, these models can provide near-optimal solutions in real-time, eliminating the need for separate optimization stages [90].
- **Complex Dependencies**
  mmWave-NOMA systems involve intricate dependencies between different optimization variables, such as user pairing and power allocation. Decoupling these tasks often overlooks how changes in one variable affect others. DL models are capable of handling these complex interdependencies, optimizing the entire system holistically and improving overall resource management [91].
- **Computations**
  DL-based models, especially those employing DRL, significantly reduce the computational burden associated with traditional optimization methods. While iterative methods may require multiple iterations to converge, deep learning models quickly approximate optimal solutions, making them more suitable for real-time applications in large-scale and dynamic NOMA systems [92].

IV. CHALLENGES AND FUTURE RESEARCH DIRECTION

The literature highlights several challenges in applying AI and DL techniques to manage resources in mmWave-NOMA environments, specifically across the five key allocation domains: power, energy, user association, bandwidth, and subcarrier allocation. These challenges stem from the complex and dynamic nature of mmWave-NOMA systems:

- **Power allocation**.
  Real-time optimization in power allocation is challenging due to the non-convex nature of the problem, especially as the number of users increases.
- **Energy efficiency**.
  energy efficiency faces difficulties in balancing efficiency with changing availability and consumption patterns, requiring real-time adjustments to maintain performance.
- **User association**.
  User association must handle fairness considerations and user mobility, which cause variations in channel conditions and impact overall system performance.

TABLE 7. Related research about DL for resource management in NOMA.

Issue	Research	Year	DL Type	Goal	Key Contribution
Power	[63]	2024	RNN	Optimized resource management and performance with efficient intelligent reflecting surface (IRS) selection and user grouping strategies.	Developed a RNN-based power allocation method for hybrid TDMA-NOMA systems, enhancing IRS selection, user grouping, and system performance under imperfect CSI.
Power	[64]	2024	DQN, DDPG, QL	Addressed user fairness and shared power allocation in an mmWave HetNet with hybrid NOMA and OMA transmissions.	Employed DQN and DDPG to tackle non-convex, NP-hard challenges in resource allocation and user fairness, accounting for imperfect SIC and hybrid NOMA-OMA transmission.
Power	[66]	2024	DDQN, DDPG	Developed a method for dynamic resource allocation to optimize spectral efficiency and QoS.	Proposed DL for resource allocation algorithm optimizing spectral efficiency and QoS for secondary users (SUs)
Power	[65]	2024	DNN	Improved the secrecy performance of cooperative NOMA systems in the presence of a passive eavesdropper.	Designed a DNN that used channel state information to predict each user's channel capacity, optimal transmit power, and power allocation coefficients.
Power	[67]	2023	DNN	Improved spectral efficiency in the massive MIMO-NOMA system with STAR-RIS.	Designed a DL framework to optimize power allocation and the phase shift matrix at STAR-RIS based on distances and channel gains in the system setup.
Power	[93]	2024	DQN	Maximized throughput while ensuring fair power consumption for extended IoT network life.	Proposed a multi-agent DQN framework to enhance throughput and ensure fair power consumption among MTC devices in uplink GF-NOMA systems.
Power	[68]	2023	DRL	Aimed to enhance client selection and resource management in federated learning using NOMA to maximize qualified clients and improve model accuracy.	Proposed DREAM-FL, a DRL approach for client selection and dynamic power allocation in NOMA-based Federated Learning, trained via simulations.
Energy	[71]	2023	DNN	Maximized EE in cooperative NOMA-enhanced cellular networks.	Used DL to optimize user pairing, subchannel assignment, and power control for maximum energy efficiency.
Energy	[72]	2024	DNN	Improved EE in massive MIMO-NOMA networks with multiple RISs.	Proposed a DL to maximize energy efficiency in massive MIMO-NOMA networks with multiple RISs.
User	[75]	2024	DDQN-DDPG, DQN	Suppressed interference and optimized resource allocation in mmWave massive MIMO-NOMA systems.	Proposed a fast-converging DRL framework to optimize user grouping and resource allocation.
User	[76]	2023	DNN	Analyzed user grouping in the downlink of a multicarrier NOMA system.	Proposed a DNN-based method for power allocation among subcarriers, assigning power to multiplexed users based on constraints.
User	[77]	2023	DQN, DDPG	Addressed resource allocation in NOMA systems, focusing on maximizing system sum rate through efficient user grouping and power allocation using deep reinforcement learning, improving on traditional methods' computational complexity and sampling inefficiency.	A Hybrid DL Framework combining Dueling DQN and DDPG addressed slow convergence and instability, significantly improving system sum rate by optimizing resource allocation in NOMA systems.
User	[78]	2023	DDPG	Addressed sum-rate and fairness maximization among NOMA-enabled CUs and DDPs while considering resource and power constraints of BS and DDT.	Proposed a DL scheme using DDPG for power allocation and interference management, supported by a multi-agent D3PG for better resource allocation and fairness, and integrated with successive convex approximation (SCA) to solve non-convex co-channel interference issues.

TABLE 7. *(Continued.)* Related research about DL for resource management in NOMA.

User	[79]	2024	DRL	Managed complexity through task scheduling and handling high-dimensional state and action spaces to approximate optimal solutions	Applied DRL to optimize task scheduling and power allocation in vehicular networks. Proposed a PPO-based task scheduling algorithm to optimize latency performance.
User	[80]	2023	DNN	Aimed to enhance spectral efficiency in beyond 5G systems with an SINR-based DL approach for user selection and power allocation in downlink NOMA.	Proposed an unsupervised DNN to maximize sum rate in a cellular downlink MISO NOMA system by combining user selection and power allocation while meeting minimum data-rate requirements.
User	[81]	2022	ML	Maximized achievable sum rate under user scheduling, analog beam selection, and resource capacity constraints.	Proposed a low-complexity ML-based scheme to solve the joint user scheduling and analog beam selection problem.
Bandwidth	[82]	2024	RL, DRL	Addressed the NP-hard problem of efficient long-term beamforming-bandwidth-power (BBP) allocation in THz-NOMA networks.	Proposed a multi-task DRL algorithm, to solve the joint BBP allocation problem in THz-NOMA networks, maximizing long-term throughput while ensuring fairness and efficiency.
Bandwidth	[83]	2023	CNN	Reduced communication delays, increased local model training times, and accelerated convergence compared to existing alternatives.	Proposed a wireless federated learning (WFL) system using MC-NOMA with adaptive flexible aggregation, enabling users to train varying iterations per round based on resources and channel conditions, increasing participation.
Subcarrier	[84]	2024	DDQN	Presented a DRL-based multi-carrier GF NOMA scheme for IoT networks to address power and sub-carrier allocation issues.	Proposed a DDQN to solve the resource allocation problem in multi-carrier grant-free NOMA systems.
Subcarrier	[85]	2023	DQN	Addressed the conflict between limited spectrum resources and growing communication demand.	Proposed DQN for radio resource allocation in a downlink multi-user cognitive radio network with slicing.
Subcarrier	[86]	2023	DQN, DDPG	Investigated resource allocation in uplink NOMA, balancing QoS for real-time users and throughput-fairness for best-effort users.	Proposed a DRL algorithm with DQN for subcarrier assignment and DDPG for power allocation.
Subcarrier	[87]	2023	DRL, DQN, DDPG	Addressed uplink NOMA IoT resource allocation, minimizing power to extend device battery life while meeting QoS requirements.	Proposed a DRL algorithm combining DQN and DDPG to reduce transmit power in NOMA systems while maintaining performance.

- **Bandwidth allocation**.
  Bandwidth allocation is constrained by spectrum scarcity and the need for effective interference management, which is particularly complex in NOMA systems.
- **Subcarrier allocation**.
  The high dimensionality of subcarrier allocation problems and variability in channel conditions make efficient resource allocation more difficult.

Additionally, there are overarching challenges:

- **Data requirements**.
  Large amounts of diverse training data are needed to develop reliable DL models, but acquiring this data is often costly and time-consuming. Synthetic data may not fully capture real-world complexities.
- **Generalization**.
  DL models frequently struggle to generalize across different scenarios and environments, limiting their applicability to varied network conditions. Models trained on specific configurations may not perform well when conditions change, especially with the high variability in mmWave channels.

In-depth analysis shows that applying DL techniques to achieve equitable resource allocation across these five domains in mmWave-NOMA systems presents several interconnected obstacles:

- **Data scarcity**.
  Each domain requires comprehensive datasets that accurately reflect the complexity of mmWave-NOMA environments. The scarcity of real-world data, coupled with the limitations of synthetic data, poses a significant challenge.
- **Optimization challenges**.
  Real-time optimization is critical but difficult to achieve, particularly for power allocation, where the non-convexity of the problem complicates efficient resource management across all domains.
- **Dynamic nature of mmWave channels**.
  The high variability of mmWave channels and the interdependence of resource allocation decisions create a computationally intensive scenario that strains the responsiveness of AI/DL models.
- **Limited applicability**.
  DL models trained for specific network configurations often struggle to maintain performance in new or evolving conditions, exacerbating the generalization problem.

To address these challenges, innovative approaches are needed, such as:

- **Multi-objective optimization**:
  Developing techniques that can balance multiple performance metrics simultaneously.
- **Transfer learning**.
  Enabling models to transfer knowledge from general mmWave-NOMA scenarios to more specific configurations.
- **Domain adaptation**.
  Facilitating automatic adjustments to channel characteristics, user behavior, or network topology.
- **Hybrid models**.
  Combining AI/DL techniques with traditional optimization methods for improved adaptability and performance.

A. FAST TIME-VARYING CHANNELS

A preliminary investigation into fast time-varying channels has been carried out as one of the key challenges highlighted for future research in this paper. One of the primary challenges in mmWave-NOMA systems is ensuring consistent and reliable communication in fast time-varying channels, especially in environments with high user mobility. Key challenges that need to be addressed include:

- **Channel estimation**.
  Fast-varying channels require frequent and accurate channel estimation to maintain communication quality, where exists a massive number of channel coefficients and severe propagation loss due to the Doppler shifts [94]. Traditional methods often struggle to keep pace with these rapid fluctuations, leading to increased errors and degraded performance. In mmWave-NOMA systems, precise channel knowledge is crucial for optimizing resource allocation and minimizing interference.
- **Beamforming and alignment**.
  Maintaining high data rates necessitates continuous beamforming adjustments due to user mobility and varying channel conditions. These frequent realignments significantly increase system complexity and operational overhead [95].
- **Interference management**.
  NOMA systems depend on effective interference management techniques, such as Successive Interference Cancellation (SIC). In fast-varying channels, dynamically changing interference conditions make it difficult to apply these techniques consistently, potentially reducing the efficiency of user pairing and resource allocation.
- **Resource allocation**.
  Optimal allocation of power, bandwidth, and subcarriers must continuously adapt to reflect rapidly changing channel conditions. Static or slow-adapting algorithms may not perform well in such environments, necessitating the development of adaptive, real-time resource management strategies.

B. POTENTIAL INTEGRATION OF MIMO TECHNIQUES IN mmWAVE NOMA SYSTEMS

The integration of MIMO techniques in mmWave NOMA systems offers significant opportunities to enhance system capacity, spectral efficiency, and overall performance. MIMO systems exploit spatial diversity and multiplexing, enabling the transmission of multiple data streams over different antennas. When combined with NOMA, MIMO allows simultaneous transmission to multiple users, improving user fairness and throughput. The challenge, however, lies in the increased complexity of resource allocation when MIMO is involved, particularly with respect to user pairing, subcarrier allocation, beamforming, and interference management. In our framework, DL, particularly DRL, has the potential to manage these complexities efficiently by jointly optimizing resource allocation across both the spatial and power domains. By learning from dynamic network conditions, DL-based models can find near-optimal solutions for beamforming, user grouping, and power allocation in MIMO-NOMA setups. Integrating MIMO techniques with the DL-driven resource allocation framework would further enhance system performance by addressing the unique challenges posed by mmWave frequencies, such as high path loss and sensitivity to blockages, while leveraging MIMO's spatial multiplexing capabilities to improve overall network reliability and efficiency. This extension will be a focus of our future work, as it promises to unlock the full potential of mmWave communications for high-demand applications in 5G and beyond.

These challenges highlight the need for future research to focus on developing adaptive deep learning models capable of addressing the dynamic and complex nature of fast-varying mmWave-NOMA environments. Hybrid approaches that combine traditional optimization techniques with machine learning could offer promising solutions to enhance system performance.

V. CONCLUSION

The increasing demand for high-speed, high-capacity wireless communications across various fields necessitates innovative solutions. In this context, mmWave and NOMA have garnered significant research attention. This study introduces the concepts of mmWave, NOMA, and DL, offering key insights into their roles in the evolution of next-generation wireless communication systems. NOMA is utilized to manage the efficient allocation of mmWave users, while DL is employed as a powerful tool to enhance this process. The paper provides an overview of how DL can address critical challenges in five key areas: power, energy, user association, bandwidth, and subcarrier allocation, while also ensuring system scalability in fast-varying wireless environments. This comprehensive approach is expected to play a foundational role in the development of next-generation wireless connectivity, paving the way for the realization of advanced 5G and beyond as ilustrated by system model.

REFERENCES

[1] W. Saad, M. Bennis, and M. Chen, "A vision of 6G wireless systems: Applications, trends, technologies, and open research problems," *IEEE Netw.*, vol. 34, no. 3, pp. 134–142, May 2020. [Online]. Available: https://ieeexplore.ieee.org/document/8869705/

[2] X. Gao, L. Dai, S. Han, I. Chih-Lin, and R. W. Heath, "Energy-efficient hybrid analog and digital precoding for mmWave MIMO systems with large antenna arrays," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 4, pp. 998–1009, Apr. 2016. [Online]. Available: http://ieeexplore.ieee.org/document/7445130/

[3] S. Han, I. Chih-Lin, Z. Xu, and C. Rowell, "Large-scale antenna systems with hybrid analog and digital beamforming for millimeter wave 5G," *IEEE Commun. Mag.*, vol. 53, no. 1, pp. 186–194, Jan. 2015. [Online]. Available: https://ieeexplore.ieee.org/document/7010533/

[4] W. Hao, M. Zeng, Z. Chu, S. Yang, and G. Sun, "Energy-efficient resource allocation for mmWave massive MIMO HetNets with wireless backhaul," *IEEE Access*, vol. 6, pp. 2457–2471, 2018. [Online]. Available: http://ieeexplore.ieee.org/document/8207349/

[5] V. Ozduran and N. Nomikos, "Performance analysis of inverse successive interference cancellation in NOMA-based communications," *Wireless Netw.*, vol. 30, no. 3, pp. 1893–1907, Apr. 2024. [Online]. Available: https://link.springer.com/10.1007/s11276-023-03618-9

[6] A. J. Muhammed, Z. Ma, Z. Zhang, P. Fan, and E. G. Larsson, "Energy-efficient resource allocation for NOMA based small cell networks with wireless backhauls," *IEEE Trans. Commun.*, vol. 68, no. 6, pp. 3766–3781, Jun. 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9032198/

[7] M. K. Hasan, M. Shahjalal, M. M. Islam, M. M. Alam, M. F. Ahmed, and Y. M. Jang, "The role of deep learning in NOMA for 5G and beyond communications," in *Proc. Int. Conf. Artif. Intell. Inf. Commun. (ICAIIC)*. Fukuoka, Japan: IEEE, Feb. 2020, pp. 303–307. [Online]. Available: https://ieeexplore.ieee.org/document/9065219/

[8] Z. Elsaraf, F. A. Khan, and Q. Z. Ahmed, "Deep learning based power allocation schemes in NOMA systems: A review," in *Proc. 26th Int. Conf. Autom. Comput. (ICAC)*. Portsmouth, U.K.: IEEE, Sep. 2021, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/9594173/

[9] J. Kaur, M. A. Khan, M. Iftikhar, M. Imran, and Q. E. U. Haq, "Machine learning techniques for 5G and beyond," *IEEE Access*, vol. 9, pp. 23472–23488, 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9321326/

[10] H. Sharma and N. Kumar, "Deep learning based physical layer security for terrestrial communications in 5G and beyond networks: A survey," *Phys. Commun.*, vol. 57, Apr. 2023, Art. no. 102002. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1874490723000058

[11] I. A. Bartsiokas, P. K. Gkonis, D. I. Kaklamani, and I. S. Venieris, "ML-based radio resource management in 5G and beyond networks: A survey," *IEEE Access*, vol. 10, pp. 83507–83528, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9851417/

[12] S. Gupta, R. Patel, R. Gupta, S. Tanwar, and N. Patel, "A survey on resource allocation schemes in device-to-device communication," in *Proc. 12th Int. Conf. Cloud Comput., Data Sci. Eng. (Confluence)*. Noida, India: IEEE, Jan. 2022, pp. 140–145. [Online]. Available: https://ieeexplore.ieee.org/document/9734183/

[13] M. A. A. Khan and H. M. Kaidi, "A comprehensive survey of machine learning techniques in next-generation wireless networks and the Internet of Things," *Ingénierie des systèmes d Inf.*, vol. 28, no. 4, pp. 959–967, Aug. 2023. [Online]. Available: https://iieta.org/journals/isi/paper/10.18280/isi.280416

[14] X. Lu, L. Xiao, P. Li, X. Ji, C. Xu, S. Yu, and W. Zhuang, "Reinforcement learning-based physical cross-layer security and privacy in 6G," *IEEE Commun. Surveys Tuts.*, vol. 25, no. 1, pp. 425–466, 1st Quart., 2023. [Online]. Available: https://ieeexplore.ieee.org/document/9961877/

[15] M. Q. Khan, A. Gaber, P. Schulz, and G. Fettweis, "Machine learning for millimeter wave and terahertz beam management: A survey and open challenges," *IEEE Access*, vol. 11, pp. 11880–11902, 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10036372/

[16] N. Van Huynh, J. Wang, H. Du, D. T. Hoang, D. Niyato, D. N. Nguyen, D. I. Kim, and K. B. Letaief, "Generative AI for physical layer communications: A survey," *IEEE Trans. Cognit. Commun. Netw.*, vol. 10, no. 3, pp. 706–728, Jun. 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10490142/

[17] M. C. Mayarakaca and B. M. Lee, "A survey on non-orthogonal multiple access for unmanned aerial vehicle networks: Machine learning approach," *IEEE Access*, vol. 12, pp. 51138–51165, 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10494323/

[18] N. Ye, S. Miao, J. Pan, Q. Ouyang, X. Li, and X. Hou, "Artificial intelligence for wireless physical-layer technologies (AI4PHY): A comprehensive survey," *IEEE Trans. Cognit. Commun. Netw.*, vol. 10, no. 3, pp. 729–755, Jun. 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10485272/

[19] T. S. Rappaport, Y. Xing, O. Kanhere, S. Ju, A. Madanayake, S. Mandal, A. Alkhateeb, and G. C. Trichopoulos, "Wireless communications and applications above 100 GHz: Opportunities and challenges for 6G and beyond," *IEEE Access*, vol. 7, pp. 78729–78757, 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8732419/

[20] V. A. Nugroho and B. M. Lee, "A survey of federated learning for mmWave massive MIMO," *IEEE Internet Things J.*, vol. 11, no. 16, pp. 27167–27183, Aug. 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10521620/

[21] J. Angjo, M. M. Tuncer, E. Akertek, H. Alakoca, M. Basaran, and L. Durak-Ata, "On the channel estimation performance of NOMA systems: Experimental implementation of real-time downlink NOMA-OFDM," in *Proc. IEEE Int. Black Sea Conf. Commun. Netw. (BlackSeaCom)*. Odessa, Ukraine: IEEE, May 2020, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/9234965/

[22] Á. Pendás-Recondo, R. G. Ayestarán, and J. A. López-Fernández, "Beamforming for NOMA under similar channel conditions including near-field formulation," *IEEE Access*, vol. 11, pp. 71250–71259, 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10177152/

[23] A. Salari, M. Shirvanimoghaddam, M. B. Shahab, Y. Li, and S. Johnson, "NOMA joint channel estimation and signal detection using rotational invariant codes and GMM-based clustering," *IEEE Commun. Lett.*, vol. 26, no. 10, pp. 2485–2489, Oct. 2022.

[24] T. Kebede, Y. Wondie, and J. Steinbrunn, "Channel estimation and beamforming techniques for mm wave-massive MIMO: Recent trends, challenges and open issues," in *Proc. Int. Symp. Netw., Comput. Commun. (ISNCC)*. Dubai, United Arab Emirates: IEEE, Oct. 2021, pp. 1–8. [Online]. Available: https://ieeexplore.ieee.org/document/9615760/

[25] C. Keawin, A. Innok, and P. Uthansakul, "Optimization of signal detection using deep CNN in ultra-massive MIMO," *Telecom*, vol. 5, no. 2, pp. 280–295, Mar. 2024. [Online]. Available: https://www.mdpi.com/2673-4001/5/2/14

[26] M. AL-Darhomi, R. S. H. AL-Musawi, and H. Al-Libawy, "Deep learning based signal detection in NOMA systems: A review," in *Proc. 2nd Int. Conf. Adv. Eng. Sci. Technol. (AEST)*. Babil, Iraq: IEEE, Oct. 2022, pp. 573–577. [Online]. Available: https://ieeexplore.ieee.org/document/10413129/

[27] B. Panda and P. Singh, "Signal detection in NOMA systems using DNN with bidirectional LSTM," in *Proc. 2nd Odisha Int. Conf. Electr. Power Eng., Commun. Comput. Technol. (ODICON)*. Bhubaneswar, India: IEEE, Nov. 2022, pp. 1–5. [Online]. Available: https://ieeexplore.ieee.org/document/10010277/

[28] B. Clerckx, Y. Mao, Z. Yang, M. Chen, A. Alkhateeb, L. Liu, M. Qiu, J. Yuan, V. W. S. Wong, and J. Montojo, "Multiple access techniques for intelligent and multifunctional 6G: Tutorial, survey, and outlook," *Proc. IEEE*, vol. 112, no. 7, pp. 832–879, Jul. 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10562043/

[29] I. Amin, D. Mishra, R. Saini, and S. Aïssa, "Power allocation and decoding order selection for secrecy fairness in downlink cooperative NOMA with untrusted receivers under imperfect SIC," *IEEE Trans. Inf. Forensics Security*, vol. 19, pp. 9406–9418, 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10700809/

[30] S. Thapar, D. Mishra, and R. Saini, "Decoding orders and power allocation for untrusted NOMA: A secrecy perspective," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*. Seoul, South Korea: IEEE, May 2020, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/9120802/

[31] C. Hu, H. Wang, C. Li, and R. Song, "Group-based successive interference cancellation for multi-antenna NOMA system with error propagation," *China Commun.*, vol. 20, no. 8, pp. 276–287, Aug. 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10238418/

[32] K. R. Chandra, S. P. Manikanta, Y. Durgachandramouli, P. S. S. N. Mowlika, C. V. V. S. Srinivas, and P. R. Budumuru, "Optimizing multi-cell NOMA system performance with power allocation and SIC analysis," in *Proc. 3rd Int. Conf. Mobile Netw. Wireless Commun. (ICMNWC)*. Tumkur, India: IEEE, Dec. 2023, pp. 1–4. [Online]. Available: https://ieeexplore.ieee.org/document/10435851/

[33] C. Thokala, K. S. Krishnan, H. Erroju, S. K. Minipuri, and Y. K. Gouti, "Power allocation in NOMA using sum rate-based dwarf mongoose optimization," *Indonesian J. Electr. Eng. Comput. Sci.*, vol. 35, no. 2, p. 683, Aug. 2024. [Online]. Available: https://ijeecs.iaescore.com/index.php/IJEECS/article/view/36197

[34] S. Trankatwar and P. K. Wali, "Power allocation for sum rate maximization under SIC constraint in NOMA networks," in *Proc. 16th Int. Conf. Commun. Syst. Netw. (COMSNETS)*. Bengaluru, India: IEEE, Jan. 2024, pp. 646–650. [Online]. Available: https://ieeexplore.ieee.org/document/10427001/

[35] X. Xu, K. Liu, P. Dai, F. Jin, H. Ren, C. Zhan, and S. Guo, "Joint task offloading and resource optimization in NOMA-based vehicular edge computing: A game-theoretic DRL approach," *J. Syst. Archit.*, vol. 134, Jan. 2023, Art. no. 102780.

[36] A. Alkhateeb, "DeepMIMO: A generic deep learning dataset for millimeter wave and massive MIMO applications," 2019, *arXiv:1902.06435*.

[37] Y. Zhang, M. Alrabeiah, and A. Alkhateeb, "Reinforcement learning of beam codebooks in millimeter wave and terahertz MIMO systems," 2021, *arXiv:2102.11392*.

[38] A. Ly and Y.-D. Yao, "A review of deep learning in 5G research: Channel coding, massive MIMO, multiple access, resource allocation, and network security," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 396–408, 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9353849/

[39] Y. Abiko, T. Saito, D. Ikeda, K. Ohta, T. Mizuno, and H. Mineno, "Radio resource allocation method for network slicing using deep reinforcement learning," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*. Barcelona, Spain: IEEE, Jan. 2020, pp. 420–425. [Online]. Available: https://ieeexplore.ieee.org/document/9016577/

[40] P. Yu, F. Zhou, X. Zhang, X. Qiu, M. Kadoch, and M. Cheriet, "Deep learning-based resource allocation for 5G broadband TV service," *IEEE Trans. Broadcast.*, vol. 66, no. 4, pp. 800–813, Dec. 2020. [Online]. Available: https://ieeexplore.ieee.org/document/8989816/

[41] W. Xu, J. An, C. Huang, L. Gan, and C. Yuen, "Deep reinforcement learning based on location-aware imitation environment for RIS-aided mmWave MIMO systems," 2022, *arXiv:2205.08788*.

[42] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Commun. ACM*, vol. 60, no. 6, pp. 84–90, May 2017. [Online]. Available: https://dl.acm.org/doi/10.1145/3065386

[43] P. Wang, E. Fan, and P. Wang, "Comparative analysis of image classification algorithms based on traditional machine learning and deep learning," *Pattern Recognit. Lett.*, vol. 141, pp. 61–67, Jan. 2021. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0167865520302981

[44] S. Kirtay, K. Yildiz, and V. G. Bocekci, "Artificial intelligence-based fair allocation in NOMA technique: A review," *Int. J. Sensors, Wireless Commun. Control*, vol. 14, no. 3, pp. 161–174, Sep. 2024. [Online]. Available: https://www.eurekaselect.com/226668/article

[45] M. H. Rahman, M. A. S. Sejan, M. A. Aziz, Y.-H. You, and H.-K. Song, "HyDNN: A hybrid deep learning framework based multiuser uplink channel estimation and signal detection for NOMA-OFDM system," *IEEE Access*, vol. 11, pp. 66742–66755, 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10167605/

[46] B. Lima, N. Fachada, R. Dinis, D. B. Costa, and M. Beko, "Uavnoma: A UAV-NOMA network model under non-ideal conditions," *J. Open Res. Softw.*, vol. 10, p. 9, Oct. 2022. [Online]. Available: http://openresearchsoftware.metajnl.com/articles/10.5334/jors.397/

[47] D. Schäufele, G. Marcus, N. Binder, M. Mehlhose, A. Keller, and S. Stanczak, "GPU-accelerated machine learning in non-orthogonal multiple access," in *Proc. 30th Eur. Signal Process. Conf. (EUSIPCO)*. Belgrade, Serbia: IEEE, Aug. 2022, pp. 667–671. [Online]. Available: https://ieeexplore.ieee.org/document/9909865/

[48] J. Hoydis, S. Cammerer, F. A. Aoudia, A. Vem, N. Binder, G. Marcus, and A. Keller, "Sionna: An open-source library for next-generation physical layer research," 2022, *arXiv:2203.11854*.

[49] N. Ye, X. Li, H. Yu, L. Zhao, W. Liu, and X. Hou, "DeepNOMA: A unified framework for NOMA using deep multi-task learning," *IEEE Trans. Wireless Commun.*, vol. 19, no. 4, pp. 2208–2225, Apr. 2020. [Online]. Available: https://ieeexplore.ieee.org/document/8952876/

[50] A. Khan, M. A. Usman, M. R. Usman, M. Ahmad, and S.-Y. Shin, "Link and system-level NOMA simulator: The reproducibility of research," *Electronics*, vol. 10, no. 19, p. 2388, Sep. 2021. [Online]. Available: https://www.mdpi.com/2079-9292/10/19/2388

[51] A. Parmar, K. Captain, U. Satija, and A. Chouhan, "Modulation classification for non-orthogonal multiple access system using a modified residual-CNN," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*. Glasgow, U.K.: IEEE, Mar. 2023, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/10118621/

[52] Y. S. Nasir and D. Guo, "Deep reinforcement learning for joint spectrum and power allocation in cellular networks," in *Proc. IEEE Globecom Workshops (GC Wkshps)*. Madrid, Spain: IEEE, Dec. 2021, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/9681985/

[53] C. He, Y. Hu, Y. Chen, and B. Zeng, "Joint power allocation and channel assignment for NOMA with deep reinforcement learning," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 10, pp. 2200–2210, Oct. 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8790780/

[54] C. Lin, Q. Chang, and X. Li, "A deep learning approach for MIMO-NOMA downlink signal detection," *Sensors*, vol. 19, no. 11, p. 2526, Jun. 2019. [Online]. Available: https://www.mdpi.com/1424-8220/19/11/2526

[55] R. Zhong, X. Liu, Y. Liu, and Y. Chen, "Multi-agent reinforcement learning in NOMA-aided UAV networks for cellular offloading," *IEEE Trans. Wireless Commun.*, vol. 21, no. 3, pp. 1498–1512, Mar. 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9520121/

[56] Z. Ding, R. Schober, and H. V. Poor, "No-pain no-gain: DRL assisted optimization in energy-constrained CR-NOMA networks," *IEEE Trans. Commun.*, vol. 69, no. 9, pp. 5917–5932, Sep. 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9448276/

[57] M. V. da Silva, R. D. Souza, H. Alves, and T. Abrao, "A NOMA-based *Q*-learning random access method for machine type communications," *IEEE Wireless Commun. Lett.*, vol. 9, no. 10, pp. 1720–1724, Oct. 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9119119/

[58] I. Budhiraja, N. Kumar, S. Tyagi, S. Tanwar, Z. Han, Md. J. Piran, and D. Y. Suh, "A systematic review on NOMA variants for 5G and beyond," *IEEE Access*, vol. 9, pp. 85573–85644, 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9433543/

[59] Y. Yuan, Z. Yuan, and L. Tian, "5G non-orthogonal multiple access study in 3GPP," *IEEE Commun. Mag.*, vol. 58, no. 7, pp. 90–96, Jul. 2020. [Online]. Available: https://ieeexplore.ieee.org/document/9162001/

[60] B. Makki, K. Chitti, A. Behravan, and M.-S. Alouini, "A survey of NOMA: Current status and open research challenges," *IEEE Open J. Commun. Soc.*, vol. 1, pp. 179–189, 2020. [Online]. Available: https://ieeexplore.ieee.org/document/8972353/

[61] S. Ma, Y. He, H. Li, S. Lu, F. Zhang, and S. Li, "Optimal power allocation for mobile users in non-orthogonal multiple access visible light communication networks," *IEEE Trans. Commun.*, vol. 67, no. 3, pp. 2233–2244, Mar. 2019. [Online]. Available: https://ieeexplore.ieee.org/document/8565925/

[62] Z. Ding, Z. Yang, P. Fan, and H. V. Poor, "On the performance of non-orthogonal multiple access in 5G systems with randomly deployed users," *IEEE Signal Process. Lett.*, vol. 21, no. 12, pp. 1501–1505, Dec. 2014. [Online]. Available: https://ieeexplore.ieee.org/document/6868214/

[63] R. Tharani, T. R. D. Kumar, C. Saravanan, R. Rahul, I. Rattankumar, and C. Gokulabalan, "Wireless power allocation for hybrid TDMA-NOMA system using deep learning recurrent neural networks," in *Proc. Int. Conf. Recent Adv. Electr., Electron., Ubiquitous Commun., Comput. Intell. (RAEEUCCI)*. Chennai, India: IEEE, Apr. 2024, pp. 1–5. [Online]. Available: https://ieeexplore.ieee.org/document/10547911/

[64] S. Sobhi-Givi, M. Nouri, M. G. Shayesteh, H. Kalbkhani, and Z. Ding, "Joint power allocation and user fairness optimization for reinforcement learning over mmWave-NOMA heterogeneous networks," *IEEE Trans. Veh. Technol.*, vol. 73, no. 9, pp. 12962–12977, Sep. 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10508101/

[65] Y. Pramitarini, R. H. Y. Perdana, K. Shim, and B. An, "Opportunistic scheduling scheme to improve physical-layer security in cooperative NOMA system: Performance analysis and deep learning design," *IEEE Access*, vol. 12, pp. 58454–58472, 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10506501/

[66] Z. Zhenyu, Z. Yong, Y. Siyu, and C. Zhenjie, "Resource allocation for cognitive network slicing in PD-SCMA system based on two-way deep reinforcement learning," *China Commun.*, vol. 21, no. 6, pp. 53–68, Jun. 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10495824/

[67] R. H. Y. Perdana, T.-V. Nguyen, Y. Pramitarini, K. Shim, and B. An, "Deep learning-based spectral efficiency maximization in massive MIMO-NOMA systems with STAR-RIS," in *Proc. Int. Conf. Artif. Intell. Inf. Commun. (ICAIIC)*. Bali, Indonesia: IEEE, Feb. 2023, pp. 644–649. [Online]. Available: https://ieeexplore.ieee.org/document/10067078/

[68] R. Albelaihi, A. Alasandagutti, L. Yu, J. Yao, and X. Sun, "Deep-reinforcement-learning-assisted client selection in nonorthogonal-multiple-access-based federated learning," *IEEE Internet Things J.*, vol. 10, no. 17, pp. 15515–15525, Sep. 2023.

[69] Z. Albataineh, A. Andrawes, N. Abdullah, and R. Nordin, "Energy-efficient beyond 5G multiple access technique with simultaneous wireless information and power transfer for the factory of the future," *Energies*, vol. 15, no. 16, p. 6059, Aug. 2022. [Online]. Available: https://www.mdpi.com/1996-1073/15/16/6059

[70] A. Andrawes, R. Nordin, and N. F. Abdullah, "Energy-efficient downlink for non-orthogonal multiple access with SWIPT under constrained throughput," *Energies*, vol. 13, no. 1, p. 107, Dec. 2019. [Online]. Available: https://www.mdpi.com/1996-1073/13/1/107

[71] Y.-Y. Guo, X.-L. Tan, Y. Gao, J. Yang, and Z.-C. Rui, "A deep reinforcement approach for energy efficient resource assignment in cooperative NOMA enhanced cellular networks," *IEEE Internet Things J.*, vol. 10, no. 14, pp. 12690–12702, Jul. 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10061583/

[72] R. H. Y. Perdana, T.-V. Nguyen, Y. Pramitarini, and B. An, "Deep learning-based energy efficiency maximization in massive MIMO-NOMA networks with multiple RISs," in *Proc. Int. Conf. Artif. Intell. Inf. Commun. (ICAIIC)*. Osaka, Japan: IEEE, Feb. 2024, pp. 382–387. [Online]. Available: https://ieeexplore.ieee.org/document/10463376/

[73] S. M. Hamedoon, J. N. Chattha, and M. Bilal, "Towards intelligent user clustering techniques for non-orthogonal multiple access: A survey," *EURASIP J. Wireless Commun. Netw.*, vol. 2024, no. 1, p. 7, Jan. 2024. [Online]. Available: https://jwcn-eurasipjournals.springeropen.com/articles/10.1186/s13638-024-02333-z

[74] H. Vidyaningtyas, "User clustering with spatial concept using supervised learning for NOMA downlink," *Buletin Pos dan Telekomunikasi*, vol. 22, no. 1, pp. 1–11, Jun. 2024. [Online]. Available: https://bpostel.kominfo.go.id/index.php/bpostel/article/view/385

[75] M. Wang, X. Liu, F. Wang, Y. Liu, T. Qiu, and M. Jin, "Spectrum-efficient user grouping and resource allocation based on deep reinforcement learning for mmWave massive MIMO-NOMA systems," *Sci. Rep.*, vol. 14, no. 1, p. 8884, Apr. 2024. [Online]. Available: https://www.nature.com/articles/s41598-024-59241-x

[76] J. Li, T. Gao, B. He, W. Zheng, and F. Lin, "Power allocation and user grouping for NOMA downlink systems," *Appl. Sci.*, vol. 13, no. 4, p. 2452, Feb. 2023. [Online]. Available: https://www.mdpi.com/2076-3417/13/4/2452

[77] Y. Liu, Y. Li, L. Li, and M. He, "NOMA resource allocation method based on prioritized dueling DQN-DDPG network," *Symmetry*, vol. 15, no. 6, p. 1170, May 2023. [Online]. Available: https://www.mdpi.com/2073-8994/15/6/1170

[78] V. Vishnoi, I. Budhiraja, S. Gupta, and N. Kumar, "A deep reinforcement learning scheme for sum rate and fairness maximization among D2D pairs underlaying cellular network with NOMA," *IEEE Trans. Veh. Technol.*, vol. 72, no. 10, pp. 13506–13522, Oct. 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10129075/

[79] Y. Cong, M. Liu, C. Wang, S. Sun, F. Hu, Z. Liu, and C. Wang, "Task scheduling and power allocation in multiuser multiserver vehicular networks by NOMA and deep reinforcement learning," *IEEE Internet Things J.*, vol. 11, no. 13, pp. 23532–23543, Jul. 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10496460/

[80] D. Kim, H. Jung, and I.-H. Lee, "User selection and power allocation scheme with SINR-based deep learning for downlink NOMA," *IEEE Trans. Veh. Technol.*, vol. 72, no. 7, pp. 8972–8986, Jul. 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10049491/

[81] Z. Zou, S. Zhao, G. Huang, and D. Tang, "Novel design of user scheduling and analog beam selection in downlink millimeter-wave communications," *IEEE Internet Things J.*, vol. 9, no. 6, pp. 4168–4178, Mar. 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9509760/

[82] Z. Hu, C. Han, Y. Deng, and X. Wang, "Multi-task deep reinforcement learning for terahertz NOMA resource allocation with hybrid discrete and continuous actions," *IEEE Trans. Veh. Technol.*, vol. 73, no. 8, pp. 11647–11663, Aug. 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10480465/

[83] W. Li, T. Lv, Y. Cao, W. Ni, and M. Peng, "Multi-carrier NOMA-empowered wireless federated learning with optimal power and bandwidth allocation," *IEEE Trans. Wireless Commun.*, vol. 22, no. 12, pp. 9762–9777, Dec. 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10123399/

[84] A. Alajmi and A. Ghandoura, "Enhancing GF-NOMA spectral efficiency under imperfections using deep reinforcement learning," *IEEE Commun. Lett.*, vol. 28, no. 8, pp. 1870–1874, Aug. 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10543128/

[85] Y. Zhang, Z. Cheng, D. Guo, S. Yuan, T. Ma, and Z. Zhang, "Downlink resource allocation for NOMA-based hybrid spectrum access in cognitive network," *China Commun.*, vol. 20, no. 9, pp. 171–184, Sep. 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10122811/

[86] M. Liu, Y. Meng, and Z. Zhang, "Deep reinforcement learning for resource allocation with mixed traffic in NOMA system," in *Proc. IEEE/CIC Int. Conf. Commun. China (ICCC)*. Dalian, China: IEEE, Aug. 2023, pp. 1–2. [Online]. Available: https://ieeexplore.ieee.org/document/10233654/

[87] H. J. Park, H. W. Kim, and S. H. Chae, "Deep learning-based resource allocation for transmit power minimization in uplink NOMA IoT cellular networks," *IEEE Trans. Cognit. Commun. Netw.*, vol. 9, no. 3, pp. 708–721, Jun. 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10064048/

[88] Y. Yin, T. Ohtsuki, G. Gui, C. Yuen, H.-C. Wu, and H. Sari, "Joint optimization of user pairing, power allocation and content server deployment in NOMA-assisted wireless caching networks," *IEEE Trans. Veh. Technol.*, vol. 72, no. 12, pp. 16866–16870, Dec. 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10185596/

[89] J. Mei, L. Yao, H. Long, and K. Zheng, "Joint user pairing and power allocation for downlink non-orthogonal multiple access systems," in *Proc. IEEE Int. Conf. Commun. (ICC)*. Kuala Lumpur, Malaysia: IEEE, May 2016, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/document/7510914/

[90] R. Wang, M. Lu, C. Hao Yu, Y.-H. Lai, and T. Zhang, "Automated deep learning optimization via DSL-based source code transformation," 2024, *arXiv:2405.03067*.

[91] Y. Gevez, Y. I. Tek, and E. Basar, "Dynamic RIS partitioning in NOMA systems using deep reinforcement learning," *Frontiers Antennas Propag.*, vol. 2, Jul. 2024, Art. no. 1418412. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fanpr.2024.1418412/full

[92] S. Wang, T. Lv, W. Ni, N. C. Beaulieu, and Y. J. Guo, "Joint resource management for MC-NOMA: A deep reinforcement learning approach," *IEEE Trans. Wireless Commun.*, vol. 20, no. 9, pp. 5672–5688, Sep. 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9400745/

[93] A. Balcı and R. Sokullu, "Fairness aware deep reinforcement learning for grant-free NOMA-IoT networks," *Internet Things*, vol. 25, Apr. 2024, Art. no. 101079. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2542660524000210

[94] J. Zhang, S. Xu, R. Yang, C. Li, and L. Yang, "HDnGAN: A channel estimation method for time-varying mmWave massive MIMO," *IEEE Trans. Wireless Commun.*, early access, Sep. 6, 2024, doi: 10.1109/TWC.2024.3451561.

[95] W. Yi, W. Zhiqing, and F. Zhiyong, "Beam training and tracking in mmWave communication: A survey," *China Commun.*, vol. 21, no. 6, pp. 1–22, Jun. 2024. [Online]. Available: https://ieeexplore.ieee.org/document/10495850/

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