IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 29 March 2024, accepted 4 April 2024, date of publication 8 April 2024, date of current version 15 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3385860

SURVEY

A Survey on Non-Orthogonal Multiple Access for Unmanned Aerial Vehicle Networks: Machine Learning Approach

MEYRA CHUSNA MAYARAKACA AND BYUNG MOO LEE, (Senior Member, IEEE)
Department of Intelligent Mechatronics Engineering, Sejong University, Seoul 05006, South Korea
Department of Convergence Engineering for Intelligent Drone, Sejong University, Seoul 05006, South Korea

Corresponding author: Byung Moo Lee (blee@sejong.ac.kr)

This work was supported in part by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by Korean Government Ministry of Science and ICT (MSIT) under Grant NRF-2023R1A2C1002656; in part by MSIT, South Korea, (ICT Challenge and Advanced Network of HRD Program), under Grant IITP-2024-RS-2022-00156345; and in part by the Faculty Research Fund of Sejong University, in 2024.

ABSTRACT The rapid evolution of wireless communication has affected unmanned aerial vehicles (UAV), which are expected to be used in diverse applications in smart cities, military operations, and cellular networks. To address the significant impacts of rapid wireless communication advancements, along with the escalating demand for user equipment (UE), multiple access technique approaches, such as non-orthogonal multiple access (NOMA), have been proposed. NOMA has the key distinguishing feature of supporting more UE, particularly UAV-enabled communication networks. Moreover, the successful implementation of such enhancements relies on the acquisition of high-quality predictions. These predictions, driven by in-depth insights derived from data, are facilitated by machine learning (ML). The integration of ML further enhances UAV capabilities to pave the way for optimized wireless communication. In this paper, we present a survey on the potential of NOMA techniques applied to UAVs using ML methods to enhance UAVs in wireless communication networks. Specifically, a basic overview of UAV and NOMA will first introduced. The role of NOMA in UAV networks is then divided into two categories: the principles and application of NOMA in UAV networks. Finally, implement ML on NOMA for UAVs by representing the diverse applications of ML systems. In addition, we highlight several open research problems as possible directions for future research.

INDEX TERMS Aerial networks, machine learning (ML), non-orthogonal multiple access (NOMA), unmanned aerial vehicles (UAV).

NOMENCLATURE

Acronym	Meaning
3GPP	3rd Generation Partnership Project
5G	Fifth Generation
A2G	Air-to-Ground
aBSs	Aerial Base Stations
ACN	Airborne Communication Network
AF	Amplify-and-Forward
AI	Artificial Intelligence
ATIS	Alliance for Telecommunications Industry Solution
BS	Base Station
CD-NOMA	Code Domain Non-Orthogonal Multiple Access
CDMA	Code Division Multiple Access
CSI	Channel State Information
D2D	Device-to-Device
D-OMA	Delta-Orthogonal Multiple Access
DF	Decode-and-Forward
DL	Deep Learning
DOA	Direction-of-Arrival
DRL	Deep Reinforcement Learning
EH	Energy Harvesting
FANET	Flying ad hoc Network
FD	Full-Duplex

The associate editor coordinating the review of this manuscript and approving it for publication was Barbara Masini.

FDMA	Frequency Division Multiple Access
FSPL	Free Space Path Loss
GBSM	Geometry-Based Stochastic Model
GS	Ground Station
HD	Half-Duplex
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
KPI	Key Performance Indicator
KL	Kullback-Leibler
LoS	Line-of-Sight
ML	Machine Learning
MIMO	Multiple Input Multiple Output
NLoS	Non-Line-of-Sight
NOMA	Non-Orthogonal Multiple Access
OFDMA	Orthogonal Frequency Division Multiple Access
OLS	Ordinary Least Squares
OMA	Orthogonal Multiple Access
OP	Outage Probability
PD-NOMA	Power Domain Non-Orthogonal Multiple Access
PS	Power Splitting
QoS	Quality of Service
RAN	Radio Access Network
RB	Resource Block
RF	Radio Frequency
RL	Reinforcement Learning
SC	Superposition Coding
SIC	Successive Interference Cancellation
SIM	Stacked Intelligent Metasurface
SINR	Signal-to-Interference-Noise Ratio
SL	Supervised Learning
SNE	Stochastic Neighbor Embedding
SNR	Signal-to-Noise Ratio
SSL	Semi-Supervised Learning
t-SNE	t-Distributed Stochastic Neighbor Embedding
TDMA	Time Division Multiple Access
TS	Time Switching
UAV	Unmanned Aerial Systems
UAV	Unmanned Aerial Vehicle
UE	User Equipment
UP	User Pairing
USL	Unsupervised Learning

I. INTRODUCTION

As wireless communication has evolved and matured, shaping the demand for unmanned aerial vehicles (UAV). In recent years, UAVs have been used in many applications. UAVs have the potential to facilitate the establishment of smart cities in urban areas, which can be categorized into monitoring, inspection, delivery, and intervention missions [1]. The stealthy, intelligent, and autonomous technology of UAVs can also be used in military applications. UAVs also emit radio frequency signals that can be captured and converted into usable energy sources for the user equipment (UE) [2]. UAVs can act as flying mobile units within a cellular network, and facilitate various applications ranging from live video streaming to items delivery [3].

UAVs also enable wide-ranging wireless connectivity across large geographical areas. They are equipped with specialized communications sensors or devices that enable collaborative swarms of UAVs to establish flying ad hoc networks (FANET) [4]. UAVs are expected to play a significant role in wireless communication networks in the future. Using airborne communication networks (ACN) UAVs can serve as aerial base stations (aBSs) to deliver wireless connectivity to ground and aerial devices in various scenarios [5]. UAVs are also equipped with apparatus for communication to provide wireless connectivity. UAVs are expected to provide ground UE with line-of-sight (LoS) through air-to-ground (A2G) communication. UAVs have shown promising prospects for new applications.

In terms of various access strategies, wireless communication systems have undergone a "revolution" throughout the last few decades and multiple access strategies have advanced over the generation of wireless communication systems. Multiple access techniques have evolved to the fifth generation (5G), including frequency division multiple access (FDMA), time division multiple access (TDMA), code division multiple access (CDMA), and orthogonal frequency division multiple access (OFDMA) [6]. To assist UAVs, existing studies have explored various multiple access techniques for next-generation wireless communication systems, such as orthogonal multiple access (OMA), non-orthogonal multiple access (NOMA), and delta-orthogonal multiple access (D-OMA) [7].

Wireless communication systems employ a variety of multiple access techniques to enable multiple UEs or devices to make efficient use of the available frequency spectrum and time slots. Multiple access techniques, such as the NOMA scheme, allow simultaneous access by multiple UEs. In [8], NOMA was employed to serve a large number of UEs. The advantages of NOMA render it a promising mechanism for communication using UAVs. These multiple access techniques are essential for ensuring reliable and effective communication in UAV operations, which is crucial for the diverse needs of various applications. NOMA can be broadly classified into two categories: code-domain NOMA (CD-NOMA) and power-domain NOMA (PD-NOMA). In CD-NOMA, code-spreading sequences are used to serve different UEs. In PD-NOMA, multiple UEs are served opportunistically based on channel conditions using a common orthogonal resource block (RB).

Machine learning (ML) is a highly effective approach that has been successfully applied to a wide range of fields. It is a subfield of artificial intelligence (AI) that involves the development of algorithms and models that enable computers to learn from data and make predictions or decisions. There are four main categories of ML algorithms: 1)supervised learning (SL); 2)unsupervised learning (USL); 3)semi-supervised learning (SSL); and 4)reinforcement learning (RL) [9], [10]. In SL, the algorithm is trained on a labeled dataset, in which the input data are paired with the correct output. USL algorithms focus on grouping sample sets into categories based on unlabeled data. SSL combines elements of SL and USL, whereas RL is concerned with training agents to make a series of decisions within an environment to maximize the cumulative reward.

The growth of UAVs has been greatly aided by extensive research on integrating various communication networks, including space-based, air-based, and ground-based communication systems [11]. Furthermore, utilizing diverse 5G communication techniques, such as shifts in architecture related to planning radio network layouts, smart antennas, air interfaces, cloud integration, and heterogeneous radio access networks (RAN) [12], can significantly enhance wireless communication performance, improve spectrum efficiency, and reduce latency. With the ability of NOMA to allow multiple users to share the same frequency and time resources and serve multiple UEs simultaneously, NOMA can increase the connectivity efficiency for both ground devices and UAVs. Applying NOMA in UAV-enabled communication networks can contribute to optimizing wireless communication by improving spectral efficiency, supporting a variety of UEs, enabling dynamic trajectory optimization, serving as relays, incorporating ML for predictive modeling, facilitating flexible deployment in emergencies, and mitigating interference challenges. Therefore, incorporating 5G communication techniques such as NOMA in UAVs using ML methods can be developed to improve wireless communication performance, improve spectrum efficiency, and reduce latency.

A. EXISTING SURVEY

Some surveys and tutorials related to UAV have been published over the past several years, along with surveys and tutorials on NOMA and ML techniques [3], [6], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26].

In, particular [3], [13] provided a tutorial on the potential advantages and benefits of UAVs in wireless communication. Likewise, in [3] UAV potential applications are presented, while in [13], the performance of UAV communication systems is analyzed across various metrics. Subsequently, in [14], ML methods have converged with mobile networking to address escalating volumes of data, adapting deep learning (DL) models within typical mobile networking applications driven by algorithms.

Later, in [16], DL was utilized to acquire remarkably precise channel state information (CSI) to improve NOMA performance. Meanwhile, in [24], the application of ML in UAV networks was presented, enabling the creation of simpler solutions for optimizing the overall network with varying capabilities in UAV processing.

In [15] the advantages and limitations of NOMA that allow different UEs to share the same frequency/time RB were discussed. In [17], NOMA was deliberated from a grant-free standpoint, allowing devices to transmit data at their discretion without scheduling requests. Similarly, [18] enhances the collective sum rate across various Internet of Things (IoT) applications by optimizing distributed power and coordinated schedules, leveraging an RL algorithm for this purpose.

To satisfy future demands, 5G wireless communication networks are being developed. In [6], multiple access schemes were considered for potential applications in next-generation wireless communications. According to [21], NOMA is the most promising scheme for addressing the needs of an increasingly large number of UEs for future wireless communication networks. Additionally, in [22], both the benefits and limitations of NOMA challenges were highlighted by applying DL while outlining the primary applications of NOMA.

The works of [20] and [23] utilized AI-aided solutions for better beyond 5G generation by discovering that the ML-based paradigm enables cost-effective UAV network deployment through resource management, routing, and access protocols. Different AI systems were presented within three classification schemes: applications, algorithms, and training [25]. Subsequently, [19] demonstrated that AI algorithms play a crucial role in addressing various challenges related to UAVs by providing potential applications for AI in UAV-based networks. Moreover, [26] delves into the realm of ML, exploring numerous applications, challenges, and techniques within ML, including image recognition, natural language processing, and recommendation systems.

The above mentioned related surveys are also presented to verify the applicability of NOMA for UAVs using the ML approach, which is not discussed in the existing related surveys. To support this survey, we provided comprehensive insights into UAVs, NOMA, and ML by showcasing an application that implements NOMA for UAVs using an ML approach. This survey provided a more comprehensive overview of the field, including new dimensions, perspectives, or applications. This survey presents the dynamic interplay of NOMA and ML in UAV communication networks and uncovers how ML models adapt to the complexity of UAV-enabled environments in NOMA systems. Additionally, this perspective could contribute to the design of more efficient and adaptive communication systems for UAVs in NOMA systems, presented with the ML integration approach. This demonstrates the actual implementation of each scope. Table 1 summarizes the highlighted related surveys and shows the main contributions of each survey.

B. PAPER CONTRIBUTION AND ORGANIZATION

Although prior research has provided various perspectives on UAV, NOMA, and ML, it is valuable to review current achievements to guide future research directions. This reflection aims to shed light on the emerging trends in this

TABLE 1. Related survey.

Reference	Year	Topic	Scope		
			UAV	NOMA	ML
[13]	2019	A comprehensive survey on potential advantages and uses of UAV in wireless communication	✓	×	×
[14]	2019	A comprehensive survey between DL and mobile networking	×	×	✓
[24]	2019	A survey of ML techniques used on UAV-based communications	✓	×	✓
[15]	2020	A comprehensive survey about orthogonal and non-orthogonal multiple access in aerial networks	✓	✓	×
[16]	2020	A survey on how DL techniques improve NOMA performance	×	✓	✓
[17]	2020	A comprehensive review on recent advances in NOMA from a grant-free connectivity perspective	×	✓	✓
[6]	2021	A survey of multiple access schemes for next-generation wireless communication systems	×	✓	×
[18]	2021	A comprehensive survey about resources allocation on NOMA using DL approach	×	✓	✓
[19]	2021	A comprehensive overview of potential AI applications within UAV-based networks	✓	×	✓
[20]	2022	A summary on AI-aided and ML approach toward UAV networks	✓	×	✓
[21]	2022	A review of NOMA that conveys aspects of 5G and B5G networks	×	✓	×
[22]	2022	A broad scope of DL-based NOMA and application on 5G communication	×	✓	×
[23]	2023	A comprehensive survey exploring AI-based autonomous UAV networks	✓	×	✓
[25]	2023	A comprehensive review providing analysis of the current and future solutions utilizing AI in UAV	✓	×	✓
[3]	2023	A comprehensive tutorial covering the potential applications and advantages offered by UAVs	✓	×	×
[26]	2023	A comprehensive survey of ML applications, difficulties, and techniques	×	×	✓
Our Survey	2023	A survey on UAV on NOMA with ML approach	✓	✓	✓

field. The objective of this paper, is to illustrate the use of NOMA for UAVs through the application of ML. In addition, we aimed to highlight a range of open research challenges.

In Section II, we provide an overview of UAV and NOMA including a summary of UAV networks and the foundational NOMA architecture. Section III focuses on the practical application of NOMA in aerial networks, examining the channel model used in UAVs, combining multiple UEs in NOMA, allocating limited resources to different UEs, selecting and grouping UEs, adaptive modulation and decoding rates, and FANET-based UAV. Section IV explores the application of NOMA to aerial networks and investigates various use cases. We provide a thorough analysis of all the relevant contributions to NOMA in aerial networks.

Section V discusses the types and evaluation of ML methods. We provide an in-depth explanation of several techniques used for each category in the ML domain. Finally, Section VI outlines the potential paths for future research in this promising field. Section VII provides a comprehensive summary and conclusions. The overall structure of this paper is shown in Fig. 1.

II. BASIC OVERVIEW OF UAV

A UAV is an aircraft that functions without a human pilot on board. Commonly known as drones, UAVs can be controlled remotely or operate autonomously through pre-programmed flight plans or dynamic automation systems. They vary in size, ranging from small recreational drones to larger military or commercial UAVs. These aircraft are equipped with a comprehensive system that oversees flight, incorporating sensors, communication devices, and navigation systems. In addition, they feature mechanisms for either remote control or self-directed navigation.

The growth in UAVs has been remarkable in various industries and applications. UAVs are popular because of their versatility and capability to execute diverse tasks, such as industrial integration by real-time remote monitoring, wireless coverage, and remote sensing. UAVs are constantly being determined in industry, leading to a continuous assessment of their functionalities across various industry sectors [27]. UAVs typically communicate by exchanging data or signals, and communication and data link attributes are elements that influence their performance and abilities. In addition to optimizing the UAV parameters to minimize energy consumption, the goal is to optimize the achievable data rate of the systems [28].

UAVs commonly function within the LoS of the ground or base station (BS) [29] and are typically equipped with a single antenna for several reasons such as range limitation, avoidance of signal blockage, and real-time communication

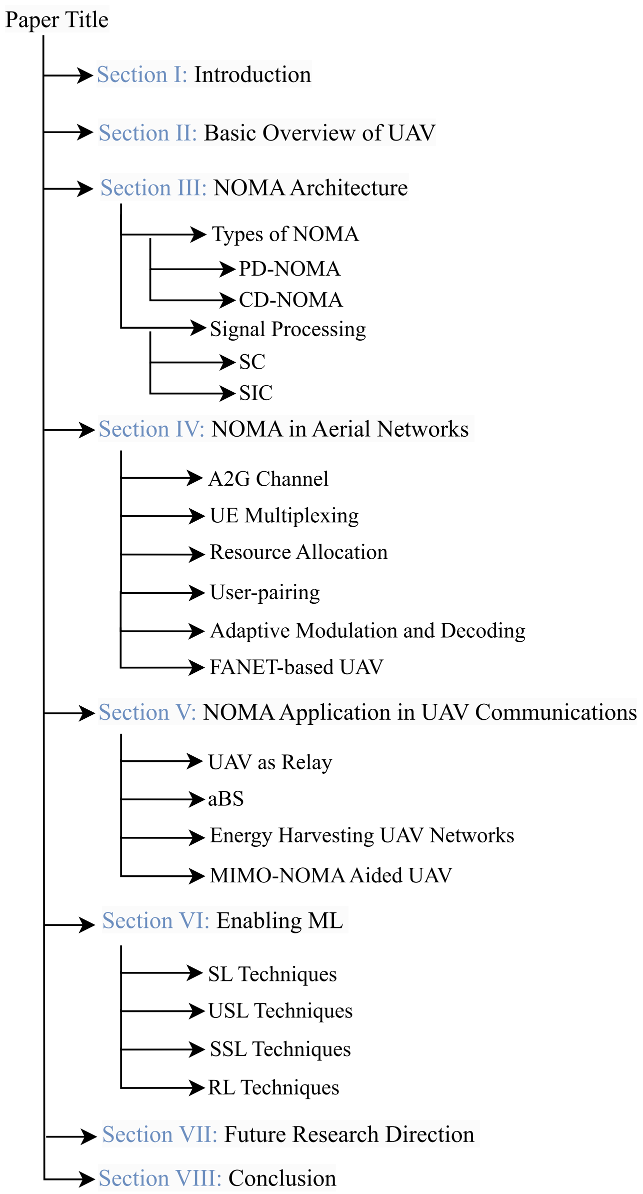


FIGURE 1. Organization of the paper.

and control. Therefore, single-antenna UAVs are often preferred because of their improved scattering in downlink communication scenarios [30]. It is not uncommon to encounter instances in which the LoS component exhibits much greater power than the reflected multipath component [6]. UAV also offer a channel estimation for operational cellular networks optimized to serve high-mobility vehicles, extending coverage for terrestrial vehicles with high-mobility or low altitude close to the cell-edge [31], [32].

UAVs rely on robust systems to detect and navigate wireless interference and environmental factors to ensure safe operation. Advanced sensing technologies can identify disruptions and minimize accident risks. Reliable and seamless operation of a UAV during long-distance operations involves maintaining a steady communication link between the UAV and its designated ground station (GS). Hence, to ensure the safe operation and effective air traffic management of UAVs, government agencies have established regulations for the use of the essential range of frequencies within the electromagnetic spectrum.

By mandating these regulations, the government aims to prevent any interference or disruption to the UAV communication systems, which could pose a significant risk to public safety. These regulations are defined in technical documents that also help to ensure that UAVs operate within designated airspace and follow proper protocols. These documents are produced by several different organizations, including the 3rd Generation Partnership Project (3GPP), Institute of Electrical and Electronics Engineers (IEEE), and the Alliance for Telecommunications Industry Solution (ATIS). These documents collectively address various aspects of unmanned aerial systems (UAS) and their integration into communication networks. 3GPP TR 23-754 focuses on supporting UAS connectivity, specifically addressing identification and tracking. 3GPP TR 23-755 explores ways to support applications that utilize UAS. IEEE Standard 1936.1 establishes a framework for drone usage across diverse applications, whereas IEEE Standard 1939.1 defines a framework for structuring low-altitude airspace, which is crucial for drone operations. ATIS I-0000069 discusses the utilization of cellular services by UAS, and ATIS I-0000071 delves into the UAS's roles in restoring communications during emergencies. ATIS I-0000074 explores the use of cellular communication to support UAS flight operations. A list of UAV operating regulations is presented in Table 2.

The bandwidth defines the amount of data that can be transferred over a given period. This ensures that the bandwidth meets the specific requirements for the intended data transfer. An insufficient bandwidth can lead to slow data transfer rates and poor UE. Therefore, the UAV must evaluate the available bandwidth and allocate resources accordingly to optimize the data transfer rates. Various approaches are used to allocate bandwidth efficiently, including the utilization of blockchain [33], ensuring an efficient quality of service (QoS) [34], and strategically placing UAVs using mathematical techniques to address optimization problems with non-convex structures [35].

While a higher bandwidth can facilitate faster data transmission and potentially reduce queuing delays, it does not inherently reduce the time it takes for data to travel, or latency, caused by physical distance or network congestion. Latency is influenced by various factors, including the network infrastructure, distance, routing, and congestion. In addition, UAV height, traffic size, and the contribution of the channel's LOS and non-line-of-sight (NLoS) components can affect latency [36]. In real-time or interactive scenarios, latency can significantly affect the responsiveness and performance of an application or service.

Maintaining strong signal strength is critical for consistent connections. The type of communication link can vary, with some UAVs relying on a direct LoS to the GS,

TABLE 2. UAV operating regulation.

Organization	Type	Title
3GPP	TR 23-754	Study on supporting UAS connectivity, Identification and tracking
	TR 23-755	Study on application layer support for UAS
IEEE	1936.1	IEEE Standard for Drone Applications Framework
	1939.1	IEEE Standard for a Framework for Structuring Low-Altitude Airspace
ATIS	I-0000060	UAV Utilization of Cellular Services
	I-0000069	Support for UAV Communications in 3GPP Cellular Standards
	I-0000071	Use of UAVs for Restoring Communications in Emergency Situations
	I-0000074	Use of Cellular Communications to Support UAV Flight Operations

whereas others use NLoS scenarios, such as relay stations or satellite communication. In interference or NLoS scenarios, ensuring reliable connections is challenging. To ensure UAV performance, UAVs use different frequency bands such as 2.4 GHz, 5.8 GHz, and 5030-5091 MHz for communication to ensure UAV performance. The specific frequency bands employed by UAVs can affect their data transmission and navigational capabilities that allow for strategic optimization, leading to less interference and spatial diversity by providing more accurate positioning information based on environmental conditions, regulatory requirements, and the specific characteristics of the positioning system employed [37]. Adaptive modulation adjusts the transmission parameters to optimize the data rates and reliability in fluctuating channel conditions. This technique can increase the average transmission rate while saving energy, which is particularly useful in ensuring operational efficiency and reliability in UAVs amid varying environmental factors and regulatory demands [38].

As technology continues to advance, the capabilities of UAVs continue to increase, making them an important asset for businesses and organizations worldwide. Understanding the concept of communication using UAVs, operating regulations, and optimizing performance is addressed in this section by explaining factors such as bandwidth, latency, signal strength, and frequency bands specific to UAV communication.

III. NOMA ARCHITECTURE

NOMA is a non-orthogonal multiple-access technique used in wireless communication systems, in contrast to other orthogonal schemes. In NOMA, nonorthogonality allows multiple UEs to share the same time-frequency resources simultaneously. In NOMA, multiple signals are transmitted simultaneously at the same time and the same frequency, with each signal intended for a specific user. This enables the simultaneous transmission of multiple signals in a non-orthogonal manner. The diagrammatic explanation of basic NOMA is shown in Fig. 2. In this section, we discuss the architecture and detailed concepts of NOMA by dividing it into two categories types of NOMA and signal processing in NOMA. Types of NOMA are divided into two types, such as PD-NOMA and CD-NOMA. Furthermore, signal processing is a fundamental attribute of NOMA by employing two techniques: SC and SIC.

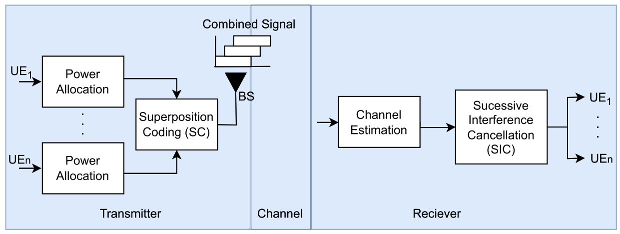


FIGURE 2. Basic NOMA explanations.

A. TYPES OF NOMA

In this section, we will discuss this configuration that involves different approaches to handling the simultaneous transmission of multiple users over the same time-frequency resources. CD-NOMA focuses on utilizing code domain techniques, while PD-NOMA operates in the power domain, each offering unique advantages and considerations within the NOMA paradigm.

1) PD-NOMA

In this section, we discuss the initial category of NOMA, known as PD NOMA. PD-NOMA operates in a relatively new domain in NOMA, which holds recency that unlike other multiple access techniques reliant on time, frequency, code domains or their combinations, PD-NOMA integrates user signals directly at the transmitter through standard coding and modulation, allowing multiple users to share the same time-frequency resources. Identification occurs at receivers using SIC. The use of non-orthogonal multiplexing through SC at the transmitter and SIC at the receiver is recognized to outperform traditional orthogonal methods and is optimal for achieving the downlink broadcast channel capacity region.

In PD-NOMA, the difference in the channel gain between users is used to create multiplexing gains by combining the transmit signals of multiple users with different channel gains. NOMA leverages the diversity in channel gains to simultaneously benefit both UEs with high and low channel gains. UEs with higher channel gains sacrifice some received power but gain significantly more bandwidth.

Conversely, UEs with lower channel gains also experience a slight reduction in received power but are allocated more bandwidth, because of interference from signals intended for UEs with higher channel gains [39].

The UEs adapt their transmission power based on the power levels assigned by the BS, ensuring that their signals can reach the BS reliably. PD-NOMA uplink power allocation involves UEs adjusting their power levels based on the assigned power resources to establish reliable communication with the BS. The BS adjusts power levels based on the UEs' channel conditions to exploit the differences in their received signal strengths, allowing for concurrent transmission within the same RB. PD-NOMA downlink power allocation aims to maximize the system capacity by allocating unequal power levels to UEs, enabling them to transmit simultaneously. The varying transmit powers and differences in the power levels assigned to different user signals within the same subcarrier. The downlink and uplink scenarios of PD-NOMA are shown in Fig. 3, in which each sub-figure provides a graph of power over the frequency that is assigned in every UE.

2) CD-NOMA

By contrast in this section, we will discuss the following part, namely CD-NOMA. The concept of CD-NOMA is an advanced version inspired by the classic CDMA systems. Building on the principles of classic CDMA systems, CD-NOMA involves multiple UEs sharing common time-frequency resources while employing unique but individualized spreading sequences for each UE [40]. However, the fundamental distinction from CDMA lies in NOMA's utilization of spreading sequences that are limited to sparse sequences or non-orthogonal sequences with low cross-correlation.

In CD-NOMA uplink transmission, UE devices adjust their transmitted power based on their assigned spreading code. The UEs modulate their data using the allocated spreading codes and adjust their transmission power to reach the BS. The UEs maintain transmission power according to their allocated codes, ensuring that their signals can be reliably received by the BS without causing excessive interference to others. CD-NOMA uplink power allocation involves UE devices that adjust their power levels to transmit their signals efficiently using assigned spreading codes.

Meanwhile, in CD-NOMA downlink transmission, the BS assigns power levels to multiple UEs based on their spreading codes. Each UE is assigned a unique spreading code, and the BS allocates power levels according to the QoS requirements and channel conditions of the UE. The BS adjusts the power to ensure reliable communication with multiple UEs, considering orthogonal or nearly orthogonal codes to minimize interference among the UEs. Power allocation in the CD-NOMA downlink ensures that UEs with weaker channels receive sufficient power for reliable reception while maintaining orthogonality between codes to enable simultaneous transmission [41]. The downlink and uplink scenarios of PD-NOMA are shown in Fig. 3, in which each sub-figure provides a graph of code over the frequency that is assigned in every UE within the same subcarrier.

B. SIGNAL PROCESSING

1) SC

SC is a key technique used in NOMA to enable simultaneous transmission and reception of multiple UEs' signals within the same frequency-time resource. The SC multiplexes the UEs' signal on the transmitter side. Superimposing many UEs at the transmitter enables the simultaneous transmission of data from multiple UEs [42]. This SC method can improve the total data rate, ensure fairness among UEs, and provide more flexibility in scheduling [43].

The SC principle involves a source generating a composite signal and involves multiple UEs denoted as k UEs. This signal is simultaneously transmitted to all UEs. The source combines signals from two UEs to create a superimposed signal. The superimposed signal at the source can be represented as,

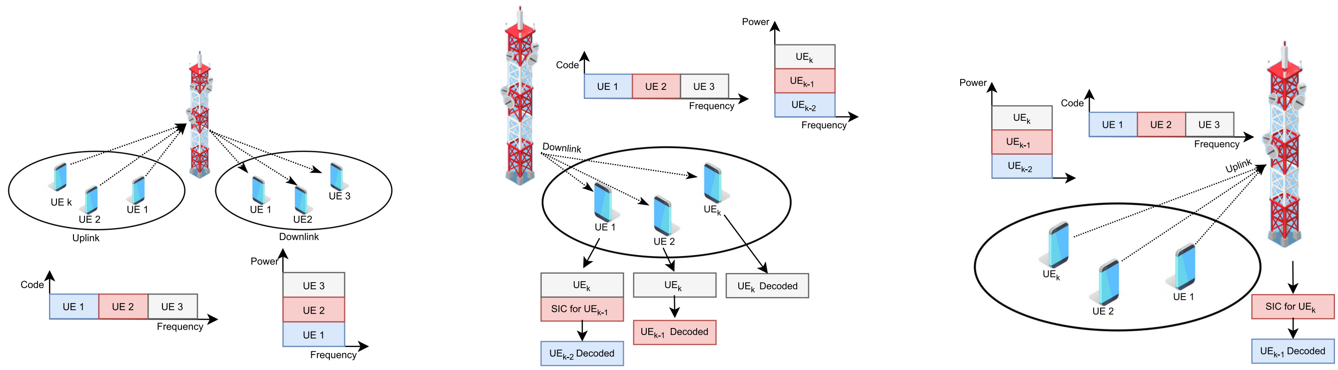
$$S_c = \sum_{k=1}^{k} \sqrt{P_k} x_k, \tag{1}$$

where S_c is the superimposed signal containing the combined signals of UE_1 up to UE_k. P_k is the total power levels of the source allocated to each UE. x_k is the signal to every UE, that may carry its data or information. This equation represents the linear combination of the signals of different UEs, scaled by the square root of their respective power allocations. The superimposed signal forms the composite transmission within the same RB, allowing multiple UEs to transmit simultaneously.

In downlink NOMA, the BS applies SC to combine signals for multiple UEs with different power levels and allocates higher power. It then allocates higher power to UEs with higher channel conditions and transmits the combined signal over the same frequency bands. Meanwhile, in uplink NOMA, the UEs apply SC to transmit with different power levels. The concept of SC in uplink and downlink is shown in Fig. 3b and Fig. 3c, in which each sub-figure provides a graph of combined signal from every UE in terms of PD-NOMA or CD-NOMA.

2) SIC

SIC decodes signals from multiple users sequentially and subtracts each decoded signal's contribution from the overall received signal to decode subsequent users. NOMA's ability to improve channel quality differences among UEs and its use of advanced SIC receivers makes this scheme the most promising technique [44]. This operation was performed on the receiver side. This system guarantees the best performance of key performance indicators (KPI) in terms of throughput, energy efficiency, and the best low-latency indicator [45]. Furthermore, because each NOMA utilizes the entire bandwidth resource, it is widely anticipated that



(a) Uplink and Downlink on NOMA (b) Downlink on NOMA (c) Uplink on NOMA

FIGURE 3. Transmission on NOMA.

NOMA will boost the system throughput. To guarantee this performance, the NOMA technique superimposes numerous UEs with varying transmission power levels on the same radio resource.

In the context of NOMA, SIC plays a crucial role in enabling the simultaneous transmission and reception of signals from multiple UEs sharing the same time-frequency resource. This contributes to the high spectral efficiency and increased system capacity of NOMA systems. SIC is a signal-processing technique used in communication systems to address interference from multiple transmissions in the same frequency band. SIC requires knowledge of the channel conditions and the order of interference cancellation. The basic idea behind SIC is to decode and remove the contribution of each UE signal one at a time in a successive manner. The process involves decoding the signal of the UE with the strongest received power, subtracting that signal from the total received signal, and then moving on to decode the signal of the next strongest UE. This iterative process continues until all UEs' signals have been decoded. By successively canceling the interference caused by stronger signals, SIC allows the receiver to retrieve signals with weaker UEs that would otherwise be masked by interference. The SIC process shows that the received signal at the receiver containing the signal from k UE can be represented as follows,

$$S_{IC} = \sum_{k=1}^{k} x_k + n, \tag{2}$$

where x_k represents the signals to every k-th UE and n represents the noise in the received signal. Then, the signals of the individual UEs are decoded sequentially, starting from the UE with the least impact on the other signals. SIC can shape the signal-to-noise ratio (SNR) into high power offsets and array gains [46].

In downlink NOMA, UEs combine the signal to perform SIC, which decodes the signal meant for itself by considering the power levels and decoding order. Subsequently, the decoded signals were canceled to remove interference for decoding the remaining signals. Meanwhile, in uplink NOMA, the BS performs SIC to decode the individual signals. The concept of SIC in uplink and downlink is shown in Fig. 3b and Fig. 3c, after receiving a combined signal from the transmitter, the receiver decodes each signal sequentially. The UE_{k+1} attempts to decode its signal first by treating UE_k signal as interference. To obtain another signal, the received signal is subtracted to cancel its impact during subsequent decoding, which can be represented as follows,

$$x_{k+1} = x - \sqrt{P_k x_k}, \tag{3}$$

where x represents the original received signal.

IV. NOMA IN AERIAL NETWORKS

UAVs typically communicate independently with the base station, and resources such as time, frequency, or code, are allocated orthogonally to different users. This widely used approach, may face challenges in terms of spectrum efficiency and support many simultaneous users. NOMA introduced a paradigm shift in UAV communication, which offers several advantages. Noma allows non-orthogonal resource sharing, enabling multiple users to use the same frequency band and time slot to improve the overall network capacity, efficiency, and ability to support a diverse range of applications for UAV communication. The principle of NOMA on aerial networks involves enabling multiple users to utilize the same frequency/time resource blocks, despite potential inter-user interference, by serving several users on a single time-frequency resource block, employing SC at the transmitter, and implementing SIC at the receiver [15], [47].

This section examines the functioning of NOMA in aerial networks by thoroughly investigating the channel model, UE multiplexing techniques, resource allocation mechanisms, user pairing strategies, adaptive modulation, and FANET-based UAV. It aims to comprehensively explore and elaborate on the operational framework and technical aspects employed within NOMA systems operating within aerial networks.

A. A2G CHANNEL

It is currently common for aircraft to rely on satellite links for internet connectivity and additionally assist communication between aircraft and GS via A2G communications. A2G communication has a lower delay than satellite communication and is reliable for emergency and control signals [48]. An overview of A2G for UAVs in aerial networks is shown in Fig. 4.

There is a path probability prediction on the A2G channel that may be described by two models: the deterministic method and the stochastic method. In the deterministic method, the LoS path is determined using a geometric operation. This method is only suitable for a specific scenario by considering well-defined parameters without considering randomness or variability using ray tracing or analytical models [49]. Meanwhile, the stochastic method involves using measurement and simulation-based empirical approaches to analyze large amounts of data, divided by the geometry based stochastic model (GBSM) and non-GBSM (Markov model) [49].

The phenomenon of multipath propagation in mobile communications is characterized by fading of the received signal, which arises from the combined effects of reflection, scattering, diffraction, and shadowing, in addition to the direct LoS path. This fading is caused by the constructive and deconstructive superposition of signal components that travel along different paths. To design and optimize wireless communication systems that can operate reliably in complex environments, it is essential to understand the nature of multipath propagation. Furthermore, the building height, width, and location in scattering propagation influence the prediction results of the LoS [50]. The A2G channel predominantly operates in a LoS-dominant mode, which empowers UAVs to offer dependable and adaptable wireless connections, opening doors for a multitude of applications and enabling them to perform diverse and intricate tasks, offering substantial benefits to various enterprises and entities.

The main path corresponds to the LoS or reflected path. Therefore, the LoS path may be calculated based on the free-space Path Loss (FSPL) model, which depends on the distance between antennas. The reflected path may be calculated by employing the principles of geometry and physics of the propagation environment and predicting the exact characteristics of the reflected paths owing to various factors.

The FSPL in wireless communication is described as the attenuation or weakening of a radio frequency signal as it travels through free space, without encountering any obstacles or reflections. The FSPL is calculated according to the formula taken from the 5G standard, that is,

$$PL_{FSPL} = 32.44 + 20\log_{10}(d) + 20\log_{10}(f) + \sigma^2, \quad (4)$$

where d and f are the distance between the antennas and the carrier frequency, respectively. σ^2 represents the zero mean and variance. However, in real-world situations, various factors, such as obstacles, terrain, buildings, and atmospheric conditions significantly affect the actual signal loss. The general path loss model is shown as follows,

$$PL = PL(d) + 10\gamma \log \frac{d}{d_0}, \quad (5)$$

where the reference path loss $PL(d)$ is evaluated at a reference distance d_0 and includes a logarithmic term for the propagation effects over the distance. And, γ represents the path loss exponent, as indicated in Table 3.

TABLE 3. Path loss exponent for different environment.

Environment	Path Loss Exponent
Free Space	2
In building LOS	1.6 - 1.8
Urban area cellular radio	2.7 - 3.5
Shadowed urban cellular radio	3 - 5
Obstructed in building	4 - 6
Obstructed in factories	2 - 3

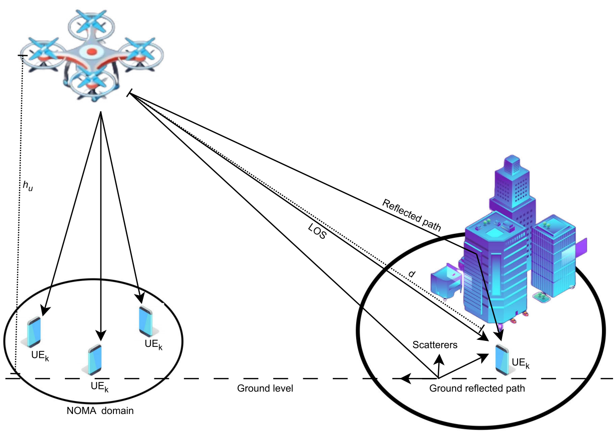


FIGURE 4. A2G channel.

B. UE MULTIPLEXING

UE multiplexing in NOMA refers to the simultaneous transmission of multiple UEs' data over the same frequency resource, thereby allowing efficient use of the spectrum. Both PD-NOMA and CD-NOMA employ UE multiplexing but through different mechanisms.

In PD-NOMA, the allocation of varying power levels to the UEs within the same frequency-time resource allows for simultaneous transmission. This strategy leverages differences in channel conditions among UEs, ensuring efficient resource utilization. In PD-NOMA, the UEs are multiplexed in the power domain by allocating different power levels to the UEs within the same RB [51]. The spectral efficiency is optimized by overlaying signals at different power levels within the same RB. At the receiver end, UE devices employ sophisticated decoding techniques, such as SIC, to decode and recover their respective signals from the multiplexed transmission received from the UAV. The receiver employs SIC to iteratively decode the signals, starting with the weakest-power UE, reducing interference as it progresses. The receiving UEs decode their information successfully by employing SIC so that UEs with good channel conditions can extract their information by eliminating other UEs' information according to the allocated power [52]. Overall, PD-NOMA's UE multiplexing enhances spectrum efficiency by accommodating diverse channel conditions.

Conversely, CD-NOMA achieves multiplexing by using orthogonal or nearly orthogonal codes for the UEs within the same frequency-time resource. This method enables multiple UEs to utilize the same resources concurrently while maintaining low interference. Features of CD-NOMA include low inter-correlation, grant-free access, and efficient spectrum usage.

Both PD-NOMA and CD-NOMA employ UE multiplexing strategies to improve spectral efficiency. While PD-NOMA adjusts the power levels, CD-NOMA uses orthogonal or near-orthogonal codes to enable the simultaneous transmission of multiple UEs. However, in PD-NOMA multiplexing, different power levels are allocated to the UE within the same resource block. Meanwhile, traditional methods rely on orthogonal resource allocation, where the UE is allocated an exclusive resource block. These distinctive approaches efficiently accommodate the UEs while minimizing interference and setting the stage for advanced wireless communication systems.

C. RESOURCE ALLOCATION

An innovative and effective approach for resource allocation in NOMA on aerial networks is to utilize multi-cluster configurations. UAV can be deployed as mobile BS and jointly optimize the transmission power, hovering location, and transmission duration of the UAV, and the maximum throughput can be achieved [53]. The aim is to meet QoS requirements despite resource limitations. This approach optimizes various aspects of a network to maximize its total throughput.

In a NOMA disposition, the allocation and distribution of various resources such as power, time slots, frequency bands, or codes among several UEs share a common communication channel or RB. Overall, NOMA allows the stacking of distinct message signals from the UEs within an NOMA cluster. The work of [54] and [55] maximizes the average throughput by optimizing the UAV trajectory and power allocation [54] or resource allocation [55]. Similarly, in [56], a power allocation algorithm utilizing NOMA was proposed to maximize the total throughput. To increase energy efficiency, in [57], resource management and allocation were carried out step-by-step. Each equivalent problem is optimized over individual variables while keeping the other variables fixed.

UAVs allocate specific time slots and frequency bands to simultaneously serve multiple UE. NOMA allows for the sharing of resources among UE. UAVs in NOMA systems can dynamically adjust resource allocation based on changing network conditions, UE requirements, or UAV mobility. This flexibility allows the system to respond in real-time to varying factors, optimizing the allocation of resources to meet the evolving demands of the network, specific UE needs, or the dynamic movement of the UAV. By continuously adapting to changing environments, systems can enhance performance, maximize efficiency, and address the dynamic nature of wireless communication scenarios. Advanced optimization algorithms are employed by UAVs to allocate resources effectively. These algorithms may consider factors such as channel quality, UE priority, interference levels, and system capacity constraints to optimize resource allocation. UEs optimize their power levels to ensure that their signals are reliably received by the BS, considering the power allocations provided by the BS for transmission [58].

Suitable resource allocation, such as scheduling and power control will ultimately lead to more efficient and robust communication systems. Scheduling algorithms can exploit multi-user diversity by selecting the most appropriate UE pairs based on channel conditions, QoS requirements, or other criteria. Power control in NOMA plays a crucial role in managing interference levels among UEs, especially in scenarios where multiple users share the same resources. Both optimizations enhance overall system capacity, reliability, and fairness. NOMA-applied UAV networks involve adaptative allocation of resources, considering UE locations, channel conditions, and communication requirements. Difference from traditional methods that used fixed resource allocation schemes. To address resource allocation in NOMA on aerial networks, Fig. 5 illustrates the resource allocation process in NOMA on aerial networks.

D. USER-PAIRING

In NOMA, the differences in the UE channel conditions owing to the near-far effect are leveraged to enhance the performance of the system. User-pairing (UP) involves selecting and pairing UEs based on their channel conditions and communication requirements. SIC is used for UEs with stronger channel conditions to decode their messages first and then eliminate the signals intended for the UEs with weaker channel conditions before decoding the messages of the stronger UEs.

To obtain the best solution for the two-UE network, the work of [59] provides a streamlined yet less complex algorithm to handle multi-UP networks using a heuristic pairing algorithm. In addition, [60] involved a location-based UP scheme aiming to optimize the transceiver association specifically for multiple UAV-aided NOMA uplinks. Strategically utilizing UP schemes aims to enhance spectral efficiency, improve throughput, and manage interference, thereby optimizing the overall performance of aerial com-

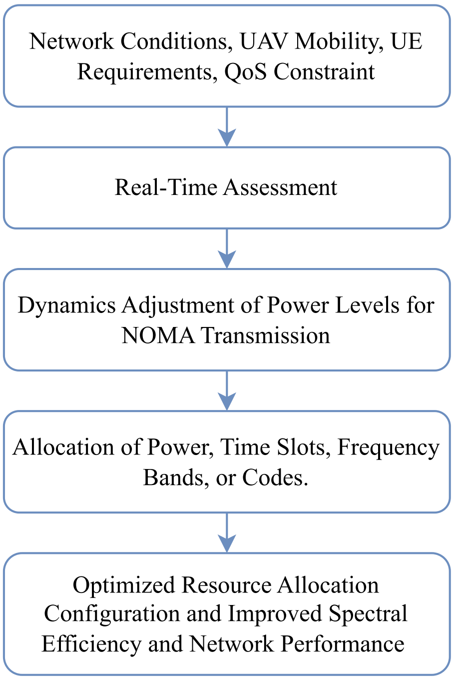


FIGURE 5. Resource allocation process in NOMA on aerial networks.

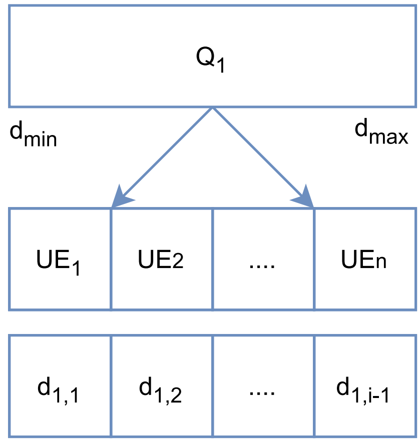


FIGURE 6. UP UAV on NOMA.

munication networks. The work of [61] suggested that a distance-based model can be utilized to establish NOMA-UP with stable channel differences.

During transmission, the channel gain primarily relies on the beam and link fading gains. In UP, based on their distance range, the UE at various distances does not have to arrange the channel gain. Within a designated region, denoted as Q, the maximum radius is represented as d_{max}, and the minimum radius is represented as d_{min}, where it is assumed that ($d_{min} \leq d_{max}$). The distance interval between every UE and BS is determined by the parameter d, which is divided into subintervals denoted by i, where ($1 \leq i \leq q$) means that $d_{1,1}$ is the distance of UE_1 in subinterval 1. And q denotes the number of partitions. The concept of UP division is shown in Fig. 6.

E. ADAPTIVE MODULATION AND DECODING

Adaptive modulation involves dynamically changing the modulation scheme based on the channel conditions to optimize the data rates and reliability. By adjusting between higher- and lower-order modulation schemes depending on the channel quality, this technique aims to enhance communication efficiency. This adaptive approach boosts spectral efficiency and overall capacity by tailoring the modulation to current conditions and efficient transmissions, even in the presence of dynamic channel disparities [62].

Real-time monitoring and advanced algorithms are crucial for this modulation adjustment, ensuring improved performance in wireless communication, particularly in UAV-assisted NOMA scenarios. The adaptive modulation system diverges from existing SIC-based systems by relying solely on instantaneous CSI rather than the received power, ensuring better system performance under fluctuating channel conditions.

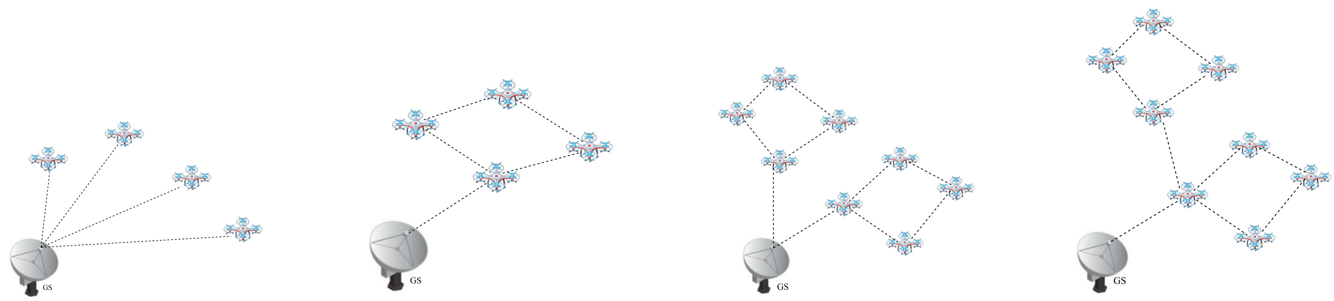
For instance, users experiencing favorable channel conditions might benefit from higher-order modulation schemes (e.g., 16-QAM), whereas users in poorer channel environments might utilize simpler schemes (e.g., QPSK) to maintain reliable communication. To achieve a successful transmission, it is recommended to use a threshold-based SNR [63].

$$\begin{cases} SNR \geq \gamma_{n(i)} & \text{scheme } m, \\ SNR \geq \gamma_{m(i)} & \text{scheme } n, \end{cases} \tag{6}$$

where γ_n and γ_m denote the threshold for different schemes, assume two modulation schemes, a higher-order modulation, n and a lower-order modulation m for all i pairs of users in NOMA systems. Modulation schemes usually found in 5G networks are considered to involve intricate designs and advanced techniques.

F. FANET-BASED UAV

The FANET architecture enables communication between UAVs and the base station without relying on fixed infrastructure [64]. This allows instant data delivery to the base station and information sharing among connected UAVs. Even if some UAVs are disconnected because of weather conditions, they can still connect to the network through other UAVs. Additionally, ad hoc networking among UAVs solves problems that arise in single UAV systems, such as short range, network failure, and limited guidance [65]. FANET can be used to achieve high-level goals and to support several applications, such as improved routing protocols and mobility [66], cooperative communication and diversity [67], and maximizing throughput on NOMA-assisted routing [68]. Likewise, in [69], a swarm of UAVs was used to improve wireless connectivity in NOMA systems, leading to high resource efficiency.



(a) Centralized Network (b) Ad hoc Network (c) Multi-group Network (d) Multi-layer Network

FIGURE 7. Architecture FANET-based UAV.

The FANET architecture comprises a central GS, to which all other UAVs are directly linked. Therefore, data communication between any two UAVs is performed through the GS. This method is called a centralized network. Meanwhile, in UAV ad hoc networks, the gateway in FANET-based UAVs possesses dual wireless communication capabilities, enabling it to operate in both short-range, low-power modes for UAV communication and long-range, high-power modes for GS communication.

The multi-group UAV ad hoc network integrates multiple UAVs within groups, linked by backbone UAVs to the GS. Intra-group communication occurs autonomously, whereas inter-group communication involves at ground station. Meanwhile, a multi-layer UAV ad hoc network comprises heterogeneous UAV groups that form ad hoc connections within each group. The lower layer manages intra-group UAV communication, whereas the upper layer handles communication between the backbone UAVs and the GS. This design minimizes GS involvement in inter-group communication and reduces the communication load and computation, making it ideal for one-to-many UAV operations. The network architecture type is shown in Fig. 7.

NOMA was designed to adapt to the dynamic topology and mobility of UAVs in a FANET. NOMA allows multiple UAVs to share the same frequency band or time slot within a communication spectrum. Signals from different UAVs were transmitted simultaneously and stacked on top of each other within the same RB. On the receiver side, UAVs decode their respective signals successively by canceling out interference from the signal of other UAVs. UAVs employ SIC techniques to decode signals by treating other signals as interferences. UAVs decode their intended signals while mitigating interference from other user signals, thereby optimizing the overall system throughput.

V. NOMA APPLICATION IN UAV COMMUNICATIONS

Advances in manufacturing technology have made UAV-aided communication a recognized emerging technique for next-generation wireless networks [70], [71]. Equipped with communication devices, UAVs can serve as BS, relays, and UEs in wireless networks. The basis of the NOMA implementation matches the goals of achieving a high spectrum efficiency by using SIC at the receivers and SC at the transmitter by UAV. To date, many studies have contributed to the adoption of NOMA in aerial networks [8], [72], [73], [74]. As evidenced by many studies, NOMA is a valuable tool for UAV-assisted communications, particularly in emergencies with more UEs.

NOMA enables the efficient transmission of data to many UEs with diverse traffic patterns. It allows UAVs to serve numerous ground UEs, each with varying power levels, by using the differences in their signal strengths. This section thoroughly investigates the utilization of NOMA in various UAV scenarios, including UAVs acting as relays, aBSs, energy-harvesting UAV networks, and MIMO-NOMA-aided UAV systems.

A. UAV AS RELAY

Therefore, it is important to find a suitable NOMA system model for UAV-aided systems. UAVs can function as relays in wireless communication systems using various relaying techniques to enhance connectivity, coverage, and overall network performance. Because UAVs can act as relays for both uplink and downlink communication, deploying a NOMA model is appropriate for UAV systems.

The work of [75] used UAVs as relays in maritime IoT networks and implemented NOMA with dynamic decoding ordering at the UAVs. This approach enables UAVs to receive multiple signals simultaneously from maritime nodes, thereby enhancing communication efficiency in maritime IoT networks. Likewise, in [76] and [77], NOMA is used for the simultaneous data transmission from the BS to the ground UEs and the UAV. Both proposed UAVs act as relays to maximize throughput and extend the coverage of the BS. In [78], the authors used NOMA to establish A2G downlink communications. To transmit data from a remote base station to multiple ground UEs, they employed a UAV as a relay. In [79] the NOMA technique and UAV-aided relay networks were combined to improve the efficiency of cell edge UEs in a macrocell network. The location of the UAV and transmission power of the UAV were optimized to minimize its power consumption. Further, a cooperative NOMA system using dedicated UAVs as relays operating in half-duplex (HD) helps connect a BS with several UE simultaneously [80]. In addition, [81] showed that D2D cooperative transmission pairs of users are simultaneously served through NOMA from the UAV, which acts as an aerial base station to improve overall communication quality. Furthermore, [82] employed ML to optimize a MIMO NOMA system with a UAV as a relay by optimizing the transmission power, UAV coordinates, and power allocation.

Network performance can vary significantly based on the relay protocol employed. UAV relays might use different protocols, such as amplify-and-forward (AF) or decode-and-forward (DF) when transmitting messages from the base station to NOMA UEs. The choice of the protocol can substantially influence the overall performance of the network. The protocol is selected to achieve optimal network performance and should be based on careful consideration of the specific requirements and constraints of the application. It is imperative to note that the suitability of a protocol depends on a range of factors, including the SNR, interference level, and target data rate. NOMA provides reliability through simultaneous relay transmissions, by involving dynamic relay decisions. ML models can learn from data to make relay decisions and optimize relay operations. The networks can contribute to the overall optimization of UAV relay operations in diverse and dynamic scenarios. Several papers contributing to UAVs as relays are listed in Table 4.

In the case of the DF relaying protocol, the UAV relay first decodes the data and then forwards it to distant UEs. During the first phase, the superimposed signal, y_1 is transmitted to the UAV relay from the BS. In the second phase, the superimposed signal, y_2 forwards the message to the NOMA UEs from the UAV relay. In particular, the transmitted signal with the DF relaying protocol for the NOMA UEs can be written as,

$$y_1 = \sum_{k=1}^{k} \sqrt{P_k} x_k x_1, \tag{7}$$

$$y_2 = \sum_{k=1}^{k} x_k x_2 + \sigma, \tag{8}$$

where x_1 and x_2 are the transmitted signals in the first and second phases, respectively. While P_k,x_k is the power, original message and σ is the noise variance.

In the case of AF protocol, the UAV relay amplifies the received signal before transmitting it to the UEs. In the first transmission phase, the superimposed signal, y_1 is transmitted and remains unchanged because it is independent of the relaying protocol. In the second phase, the superimposed signal, y_2 the original message, is multiplied by a variable gain, which is a function of the transmit power of the UAV relay. The variable gain is defined as, $G = \frac{1}{\sqrt{P|h_{BS-UAV}|+\sigma^2}}$ where, P, $|h_{BS-UAV}|$ and σ represents the power, channel gain BS to UAV, and noise variance. The transmitted signal from the relay to the destination with the AF protocol for the NOMA UE can be written as,

$$y_1 = h_{sr} x_s + n_r, \tag{9}$$

$$y_2 = y_1 G, \tag{10}$$

where h_{sr}, x_s, and n_r are the channel gains between the source and relay and the signal transmitted from the source and noise at the relay, respectively.

B. aBS

UAVs can support standard communication networks by serving as flying base stations or aBSs—a new paradigm for UAVs to be used in natural disaster management. In recent literature, extensive exploration of employing UAVs in disaster management for wireless communication support has been thoroughly investigated [83], [84]. In emergency and public safety circumstances, UAVs can act as aBSs to supply additional capacity to hotspot locations and provide network coverage [85]. Moreover, [86] discovered that employing NOMA to intelligently integrate aBSs benefits terrestrial UEs by increasing the spectrum efficiency and system sum rate.

The study of [87] focused on cellular-connected UAVs employed for surveillance, considering a trajectory-based movement in PD uplink aerial-terrestrial NOMA to enable simultaneous uplink transmissions. The work of [88] presents UAVs as aBS in the NOMA environment to enhance network performance, reduce transmission delays, and utilize deep reinforcement learning (DRL) to allow UAVs to interact with their environment. Furthermore, [89] provided an ML-based framework for the predictive deployment of UAVs as aBS utilizing a long short-term memory-based algorithm and comparing multiple access techniques, including rate-splitting multiple access (RSMA), FDMA, TDMA, and NOMA. UAVs as aBS can be supported by several sources, such as satellites or BS. Several studies that contributed to EH are presented in Table 5.

The versatility of UAVs can be utilized for positioning at particular spots or relocated as necessary to areas that require stronger connectivity. As adaptable aBSs, UAVs carry communication equipment similar to traditional ground-based stations, including antennas and signal processing. Positioning UAVs closer to ground UEs, can provide better signal strength and quality, reduce interference, and increase the total network capacity. Depending on the network limitations, external factors, or particular communication requirements, UAVs can modify their parameters and positions. The UAV acts as an aBS, providing broader connectivity to ground users. Traditional methods typically involve a fixed ground-based infrastructure. UAV-enabled systems introduce dynamic and flexible aerial platforms that can be strategically positioned to improve coverage, mobility, and efficient resource utilization. The improved coverage by the aBSs is shown in Fig. 8.

In a NOMA environment that can serve many UEs, UAVs serve as flexible and mobile BS that can dynamically position themselves for improved coverage. To optimize

TABLE 4. UAV as relay contribution.

Reference	Objective	Contribution	Scope		
			UAV	NOMA	ML
[75]	DF Protocol	Enhancing the efficiency of maritime IoT networks by employed multiple UAVs in NOMA paradigm	✓	✓	×
[76]	AF Protocol	Maximize overall throughput in UAV relay systems	✓	×	×
[77]	DF Protocol	UAV act as relay to improve coverage for UE in NOMA systems	✓	✓	×
[78]	DF Protocol	Minimize the power consumption of UAV in NOMA systems	✓	✓	×
[79]	DF Protocol	Enhance the performance of the cell edge users by incorporating NOMA techniques in UAV relay-aided networks	✓	✓	×
[80]	AF Protocol	Provide better spectral efficiency and user fairness in NOMA-based relaying networks	×	✓	×
[81]	DF Protocol	Employing ML to improve D2D communication quality served through NOMA from UAV	✓	✓	✓
[82]	DF Protocol	Employing ML for optimization on MIMO-NOMA system UAV relay	✓	✓	✓

TABLE 5. aBS contribution.

Reference	Objective	Contribution	Scope		
			UAV	NOMA	ML
[84]	BS	Deploying UAV as aBS in natural disaster to improve networks	✓	×	×
[85]	BS	UAV as aBS as a solution to offloading	✓	×	×
[86]	Satellite	Served terrestrial users by adopted NOMA techniques	✓	✓	×
[87]	BS	Utilize UAV as aBS for surveillance in NOMA transmission	✓	✓	×
[88]	BS	UAV as aBS for the ground user in NOMA and OMA along with DRL	✓	✓	✓
[89]	BS	ML-based for predictive deployment of UAVs as aBS and comparing multiple access techniques	✓	✓	✓

UAV trajectories ML algorithms can predict based on user locations, communication demands, and interference patterns. In addition, UAVs can operate as intelligent and adaptive aerial base stations, providing efficient, reliable, and dynamically optimized wireless communication services to ground users in a variety of scenarios.

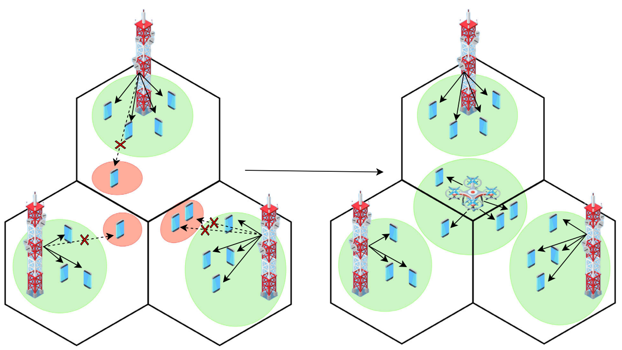


FIGURE 8. UAV as aerial base stations.

C. ENERGY HARVESTING UAV NETWORKS

There has been a recent interest in implementing radio frequency (RF) for energy harvesting (EH)/scavenging or radio frequency-energy harvesting (RF-EH). The RF-EH is a promising technique for powering energy-constrained wireless networks. The RF-EH converts the received RF signals into electricity and provides a power solution for energy-constrained wireless networks. It has a sustainable power supply from a radio environment and is used in various applications, such as wireless sensor networks [90], wireless body networks [91], and wireless charging systems [92].

UAVs are utilized as power sources for RF-EH by transmitting RF signals from the UAV to be captured and converted into electrical power by specialized devices on the ground. The UAV was equipped with a high-power RF transmitter capable of emitting RF signals toward designated RF EH devices on the ground. By integrating EH into UAVs in NOMA systems, these aerial platforms can overcome energy limitations, operate for extended periods, and enhance their overall performance and reliability in wireless communication networks. By reducing reliance on conventional power sources, EH enhances the overall performance and capabilities of UAVs operating in NOMA-enabled wireless communication networks.

To minimize the total energy consumption, in [93] UAV-enabled wireless communication systems with EH were investigated. In particular, the UEs can harvest energy for data transmission, and the UAV transfers energy to the UEs in the HD or full-duplex (FD). To serve more users at the systems, in [94], an uplink and downlink NOMA system was examined using EH, uplink NOMA for EH in the wireless system while multiple users are served in the downlink. The work of [95] shows the EH capabilities of NOMA by dividing UEs into several groups and employing SIC to overcome issues and determine the design parameters. Including the capabilities of minimum power needed to fulfill both the minimum rate and harvest energy requirements for each user.

However, the UAV-enabled NOMA system in [96] investigated the system performance of EH on UAV-enabled IoT and applied NOMA to both hops to improve throughput. Additionally, [97] proposed a cooperative communication model in which the UAV acts as a relay, using AF and DF protocols to evaluate outage and ergodic capacity in NOMA systems.

The study in [98] utilized deep reinforcement learning (DRL) to identify the optimal solution for EH time scheduling. In addition, [99] explored the integration of UAV-assisted NOMA within IoT systems, in which the UAV serves as a relay. The focus is on a scenario with several IoT device clusters that cannot independently process their tasks according to the RF-EH. Similarly, [100] employed an EH-based IoT-inspired UAV-assisted overlay cognitive NOMA system for a cooperative spectrum-sharing transmission scheme. Simultaneously, in the context of UAV-assisted device-to-device (D2D) communication.

Additionally, in UAV networks, where resources are often limited, NOMA allows multiple users to share the same time-frequency resources simultaneously, leading to improved spectral efficiency, increased user capacity, and optimized resource allocation for EH. NOMA enables a more efficient utilization of the available spectrum, leading to increased throughput and better overall network performance. UAVs operate in dynamic and unpredictable energy environments, NOMA flexibility in resource allocation can be leveraged to prioritize users with higher energy requirements, ensuring efficient utilization of harvested energy. ML-based rate-splitting models can adapt to changing energy conditions, optimizing NOMA parameters for energy-efficient communication. UAVs can operate more efficiently, which enhances the sustainability and autonomy of UAV missions in scenarios where EH is a consideration.

In NOMA-based UAV networks, the received signal is split for EH and data transmission, using three approaches: power splitting (PS), time switching (TS), and a hybrid protocol. The PS, TS, and hybrid methods vary in power and time allocation between EH activities and data transmission. Several studies that contributed to EH are presented in Table 6.

1) TS PROTOCOL

In this protocol, the receiver switches between information processing and EH. The TS protocol uses a time-separation mode in which energy and information transfer are assigned to two separate time slots in each time block and operate in the network area for the same time block T. A block diagram of the TS protocol is presented in Fig. 9a. Thus, the received power from the EH process using the TS protocol is expressed as,

$$E_{TS} = \eta \alpha PhT, \tag{11}$$

$$P_{TS} = \frac{E_{TS}}{(1-\alpha)T}, \tag{12}$$

where α represents the time switching factor, indicating the proportion of time or duration within a designated time slot devoted to EH. In the first αT time slot, the UE harvests energy from the RF-signal UAVs transmitted in TS protocol, where $0 \leq \alpha \leq 1$. Then, in the $(1-\alpha T)$ time slot, the UE transmits information in the form of data using the harvested energy. Where, η, P, h represent the harvesting efficiency factor, power, and channel gain.

2) PS PROTOCOL

This protocol allows for the simultaneous use of received signals for both EH and information decoding or data transmission. The power splitting protocol enables the UE to harvest energy while simultaneously decoding information from the received signals in a single time slot. A block diagram of the PS protocol is shown in Fig. 9b. Thus, the received power from the EH process using the PS protocol is expressed as

$$E_{PS} = \eta \beta PhT, \tag{13}$$

$$P_{PS} = \frac{E_{PS}}{T}, \tag{14}$$

where β represents the power splitting factor, indicating the ratio or division of the power of the received signal between EH and information decoding or transmission. In the first part, βP is used to harvest energy, whereas the second part $(1-\beta P)$ is used to transmit information in the form of data transmission using the harvested energy, where $0 \leq \beta \leq 1$. This process is performed in a one-time slot, T. Where, η, P, h represent the harvesting efficiency factor, power, and channel gain, respectively.

3) HYBRID PROTOCOL

This protocol is a combination of existing EH protocols (PS and TS). A block diagram of the hybrid TS-PS protocol is shown in Fig. 9c. Thus, the power received from the EH process using the hybrid protocol is expressed as,

$$E_h = \eta \alpha PhT + \eta \beta Ph(1-\alpha)\frac{T}{2}, \tag{15}$$

$$P_h = \frac{\eta \alpha PhT + \eta \beta Ph(1-\alpha)\frac{T}{2}}{(1-\alpha)\frac{T}{2}}, \tag{16}$$

$$= \eta \left(\frac{\alpha}{(1-\alpha)/2} \right) Ph + \eta \beta Ph \tag{17}$$

In the first αT time slot, the UE harvests energy in the TS protocol. Then, in $(1-\alpha T)$ UE harvests energy in the PS protocol, and during this period, the UE transmits information in the form of data transmission using the harvested energy. Subsequently, the UE forwards the information to the

TABLE 6. EH contribution.

Reference	Objective	Contribution	Scope		
			UAV	NOMA	ML
[93]	TS Protocol	Minimize total energy consumption of UAV networks	✓	×	×
[94]	PS Protocol	OP performance for uplink NOMA for EH and downlink NOMA to serve users	×	✓	×
[95]	PS Protocol	NOMA assesses the transmit power consumption of each user within a group	×	✓	×
[96]	Hybrid Protocol	Applied NOMA to improve throughput in UAV-enabled IoT	✓	✓	×
[97]	TS Protocol	Characterize the outage and ergodic capacity performance in UAV relay networks employing NOMA	✓	✓	×
[98]	PS Protocol	Employed DRL for EH in UAV-assisted networks	✓	×	✓
[99]	TS Protocol	Performance on IoT device with UAV as relay in NOMA using RF-EH	✓	✓	✓
[100]	PS Protocol	Using the deep neural network in UAV-enabled NOMA system utilizing EH for OP prediction	✓	✓	✓

destination. Where, η, P, h represent the harvesting efficiency factor, power, and channel gain, respectively.

D. MIMO-NOMA AIDED UAV

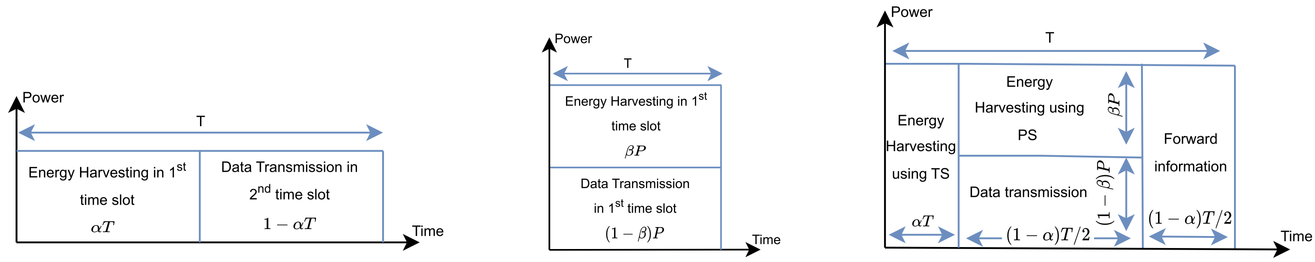
MIMO systems employ multiple antennas at both ends of a communication link to transmit and receive several data streams using the same frequency channel. MIMO enhances reliability and improves data rates, whereas NOMA is employed to cater to a large number of users with limited spectrum resources. Incorporating MIMO-NOMA-assisted UAVs has shown latency reduction [101], for optimal resource allocation. In [102], UAV-assisted MIMO-NOMA was utilized to maximize sum capacity while meeting the UE QoS requirements, impacting transmission rates and power allocation. Additionally, concerns arise with errors in cases where the interference power aligns with the UAV power in [103].

On the other hand, massive MIMO systems significantly increase the number of antennas at both the transmitting and receiving ends compared to conventional MIMO systems, making massive MIMO-NOMA are promising technology for future mobile networks. Massive MIMO technology enhances spectral efficiency and energy efficiency by effectively managing interference and noise through large-scale antenna deployment and appropriate power scaling laws [104], as well as by combining scheduling, power control, and dropping techniques on the IoT [105]. Furthermore, in [106], the capacity of a Massive MIMO-backed IoT system was evaluated, suggesting that increasing the number of service antennas or reducing IoT device numbers can enhance system performance, specifically in reducing blocking probability. Several studies about massive MIMO have been conducted in [105], [106], [107], [108], and [109].

The study of [110] introduced MIMO systems that employ ML to generate hybrid beams based on channel parameters and user feedback by addressing challenges such as minimizing pilot overhead, improving channel estimation accuracy, and reducing power consumption and hardware complexity through antenna selection and reinforcement learning-based hybrid beamforming. In [111], a large number of UAVs were investigated, with one UAV leading and employing a NOMA beam and a DL-based NOMA-grouping-aware fast transmit beamforming optimization scheme. In [112], NOMA and spatial modulation were combined, utilizing MIMO to employ UAVs as connectivity services to enhance energy efficiency. In addition, [113] presented a DL-based approach for modeling a UAV communication channel with MIMO and NOMA in urban areas. Furthermore, [114] explored a UAV-enabled network and multiple UAVs acting as aerial base stations, employing NOMA in a MIMO architecture and utilizing an ML-based algorithm for efficient and low-complexity optimization.

In contrast, a base station with multiple transmit antennas catering to more than one UE as much as i to receive antenna, r_i where the range from m to n, each with $r_i(i = m, n)$ receives antennas, even when $r_m = r_n = 1$. However, in the context of NOMA, where each user treats its signal as noise, and then calculates the signal-to-interference-noise ratio (SINR), incorporating interference might lead to an overestimation of co-channel interference effects. To manage this, SIC eliminates their signal interference and decodes their signals with SINR, which introduces an added constraint $R_{n \to m} > R_{m \to m}$. This prerequisite guarantees that after successfully decoding m UE messages, UE n can effectively demodulate and cancel the transmission of the UE. MIMO is considered to be aligned when the number of transmitting antennas matches the number of receiving antennas, which is represented as $t = r_m = r_n$. In addition, all channel gain matrices are identity matrices in this scenario.

The work of [115] principally divided the applications of MIMO-NOMA into two categories, beamformer-based and cluster-based. In MIMO-NOMA cluster-based structures, each UE group (cluster) is formed for the NOMA operations. To implement the signal alignment strategy, given the maximum number of clusters, Q. Consequently, the UAV transmits Q x 1 signals vector to UE. In beamformer-based



(a) TS Protocol (b) PS Protocol (c) Hybrid TS-PS Protocol

FIGURE 9. RF-EH protocol.

structures, the matrices can be designed to ensure zero intercell and inter-cluster interference, the transmit beamformer, v_k and assume that $||v_k^i||_2 = 1$ with UE i in k resources.

Implementing MIMO-NOMA in UAV communication systems requires addressing challenges such as hardware complexity, signal processing intricacies, and synchronization issues. However, the potential benefits in terms of spectral efficiency, multi-user connectivity, and improved throughput make MIMO-NOMA a promising technology for enhancing communication in UAV networks, enabling efficient and reliable data transmission in various operational scenarios. NOMA involves dynamic beamforming and grouping users for efficient communication in simultaneous transmissions for UAVs. Meanwhile, ML algorithms can facilitate intelligent user grouping and optimize beamforming using NOMA parameters for efficient communication. This can benefit from enhanced spectral efficiency, dynamic resource allocation, and adaptive power control. Several studies that contribute to MIMO are listed in Table 7.

VI. ENABLING ML

ML's ability to learn and adapt is proven through its application of algorithms that enable systems to analyze data, recognize patterns, and make predictions or decisions [116]. By dynamically adjusting their behavior, improving performance, and making informed decisions based on evolving patterns and data, making it a viable paradigm for next-generation networks. ML is a method for machines to learn patterns and make predictions or decisions without being explicitly programmed for each task. As several articles have reported [117], [118], once the training phase of an ML system is completed, the system can swiftly and efficiently perform a diverse range of tasks within milliseconds. This rapid execution is a result of the ML model learning from the training data, enabling it to make quick and accurate predictions or decisions in real-time applications. The trained model captured the patterns and relationships in the data, can seamlessly processed new inputs, and provided outputs with minimal delay.

ML stands as a robust and pioneering domain in the field of AI. ML has surged remarkably owing to technological advancements, enhanced computational capabilities, and the abundance of data. Its ability to enable machines to learn from and identify patterns in data has revolutionized data processing, making it more efficient and accurate. Consequently, it has become a pivotal tool across diverse sectors, offering valuable insights from data analysis for informed decision-making.

The core idea of ML is to build models that can identify patterns in data and make predictions or decisions based on those patterns. Instead of being explicitly programmed to perform a task, an ML system is trained using large amounts of data, allowing it to generalize and make predictions or decisions regarding new, unseen data. ML is employed for predictive modeling of user behavior, channel conditions, and resource demand. Traditional methods often lack predictive capabilities, whereas NOMA with UAVs leverages ML for proactive resource management, improving efficiency and responsiveness.

Virtually every industry has begun to integrate ML into its operations. The Industry 4.0 paradigm encourages the use of intelligent sensors, devices, and machines to establish smart factories that continuously collect data on production. ML techniques can be utilized to process collected data and generate actionable intelligence that can improve manufacturing efficiency without requiring significant changes to the resources being used. This approach enables real-time monitoring, predictive maintenance, and adaptive production strategies, thereby fostering a more agile and responsive manufacturing ecosystem. The seamless integration of ML in Industry 4.0, not only enhances operational efficiency but also opens avenues for innovation, optimization, and data-driven decision-making across diverse industrial sectors. It has applications in various fields, including healthcare, finance, autonomous cars, natural language processing, and recommendation systems [119]. Furthermore, ML techniques offer predictive insights that enable the recognition of intricate manufacturing patterns and aid in creating intelligent decision support systems for tasks such as ongoing inspections, predictive maintenance, quality improvement, process optimization, supply chain oversight, and task scheduling in manufacturing [120]. Additionally, ML has been applied in the monitoring of complex systems, such as fault detections [121], [122].

The work of [123] introduced a three-stage joint channel decomposition and prediction framework for CSI

TABLE 7. MIMO contribution.

Reference	Objective	Contribution	Scope		
			UAV	NOMA	ML
[101]	Cluster based	Minimize user delay by jointly apply UAV, MIMO, and NOMA	✓	✓	×
[102]	Cluster based	Utilize UAV as aBS to optimize Qos in MIMO-NOMA communication	✓	✓	×
[103]	Cluster based	MIMO-NOMA assisted UAV utilize GBSM to evaluate the performance	×	✓	×
[104]	Cluster based	Enabled UAV MIMO-NOMA through power scaling laws	✓	✓	×
[114]	Cluster based	UAV as aBS using NOMA in MIMO architecture utilize ML based for optimization	✓	✓	✓
[110]	Beamformer based	Generate hybrid beams in MIMO environment with ML for enhancing array gain	×	×	✓
[111]	Beamformer based	Optimization on a large number of UAV over NOMA beam using Dl-based	✓	✓	✓
[112]	Beamformer based	Utilize UAV as a connectivity service in NOMA and employs MIMO	✓	✓	×
[113]	Beamformer based	Model the UAV communication channel DL based with MIMO-NOMA in urban areas	✓	✓	✓

acquisition, surpassing traditional algorithms, and demonstrated resilience to estimation errors, by noise elimination using deep learning through extensive data training. Similarly, [124] introduced a location-aware imitation environment-based DRL algorithm to optimize joint beamforming and enhance signal transmission quality in wireless communications.

As discussed in [81], a UAV placement strategy is aimed at improving an integrated UAV-D2D NOMA cooperative network, employing SSL techniques that integrate both SL and USL techniques. Likewise, in [125] the outage performance of a NOMA-enabled UAV network using various ML techniques was conducted on a generated dataset incorporating multiple network parameters.

It is possible to train SL and USL to obtain a new model representation [126]. As demonstrated by the DL task revolution, RL is effective in obtaining useful representations using multi-layered neural networks to extract advanced data features [127], [128]. These cover several categories and Fig. 10 shows a basic representation of the broad ML categories. The main purpose of most ML techniques is to create an optimization model that can identify the parameters needed to optimize the objective function. Robust optimization methods for big data are essential to the performance of these models. These techniques carry ML forward, improving efficiency and opening up new avenues for research in a variety of domains. Generally, optimization methods are essential for AI applications. The adaptability and learning capabilities of ML contribute to the effectiveness of NOMA in addressing the challenges of UAV communication networks. ML provides an accurate prediction regarding the UAV-NOMA environment, data rate requirements, trajectories, UE demands, and communication networks. The potential benefits of integrating ML with NOMA in UAV communication networks can optimize overall system performance. In this section, we describe four primary types of ML, SL, USL, SSL, and RL. Moreover, we explored the specific methods related to each group, providing comprehensive explanations.

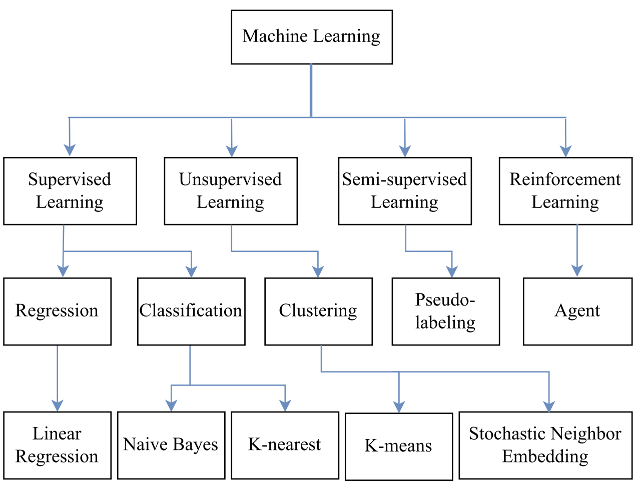


FIGURE 10. ML categories.

A. SL TECHNIQUES

SL is a type of ML where the model learns from labeled training data, meaning that the data used for training have input output pairs. The primary goal is to learn a mapping function from input to output. This learned function can then be used to predict or classify new unseen data.

SL gathers a dataset with the inputs and their corresponding outputs. Preprocessing was performed by cleaning, normalizing, and preparing the data for training. Choose an appropriate algorithm or model based on the nature of the problem. The labeled data were then used to train the model. The model adjusts its parameters to minimize the difference between predicted and actual outputs. The performance of the model was assessed using a separate dataset (validation or test data) that was not used during training. Once the model is trained and evaluated, it can make predictions or classify on new, unseen data. SL has also been applied in academia [129], health [130], management [131], and network security [132].

SL can be classified into two types: regression and classification. Both types of networks can be used in wireless networks. The potential of the ML approach lies in its ability to extract knowledge from operational UAVs and swiftly predict design parameters during the conceptual phase of UAV development. In [133], frameworks were formulated based on five different regression models using a UAV database. In [134], a dynamic communication network for UAVs was generated by modifying the classification. In [135], UAVs were used to select the optimal BS to enhance the overall performance by training the SL techniques.

Through SL, UAV-NOMA systems can enhance the efficiency. Labeled data can be utilized to learn and discern patterns, allowing for dynamic resource allocation within NOMA systems. Predict and adapt to interference patterns by adjusting the transmission parameters, ensuring the reliability of communication. Optimize signal reception and QoS parameters, including anticipation and assurance of low latency, high throughput, and dependable connectivity based on historical performance data. Implementing resource optimization strategies to effectively extend UAV flight time.

1) REGRESSION

Regression is typically used for predictive analysis. The simple linear regression for a simple input feature represents a linear relationship between input variables x, and output variables $\hat{y}$. Here, m is the slope and b is the y-intercept. It can be expressed as,

$$\hat{y} = mx + b, \tag{18}$$

During the training process, the objective is to determine the optimal values for the coefficients m and intercept b that minimize the difference between the predicted values ($\hat{y}$) and actual target values y. This is typically achieved by utilizing optimization techniques such as ordinary least squares (OLS) or gradient descent to adjust the coefficients and minimize the error between the predicted and actual values.

The coefficients or parameter θ of the linear model are calculated. Using the closed-form solution of the OLS method in linear regression, can be expressed as

$$\theta = (X^T X)^{-1} X^T \vec{y}, \tag{19}$$

where X denotes the input feature, X^T denotes the transpose of the matrix X, and $\vec{y}$ is the vector of the target values. Using the gradient descent, can be expressed as

$$\theta_j = \theta_j - \alpha \nabla J(\theta), \tag{20}$$

$$\theta_j = \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_0(x^i) - y^i) x_j^{(i)}, \tag{21}$$

where h_0 represents the predicted value for the ith training example, x^i and y^i denotes the actual target value and feature value with $\nabla J(\theta)$ measure the difference between predicted and actual values, then repeat simultaneously for all j, where α denotes the learning rate that specifies the step size for each iteration, m denotes the number of training. The regression result are shown in Fig. 11a.

2) CLASSIFICATION

In the classification, is used to predict the discrete values. The classification result are shown in Fig. 11b. The classification is explained below.

1) Naïve Bayes
   Naïve Bayes utilizes labeled data to measure probabilities and perform classifications using the principles of Bayes' theorem. It determines the likelihood of a particular event occurring on the basis of the probabilities associated with other related events. From [129], the Bayes rule can be defined as

$$P(A|B) = \frac{P(A|B)P(A)}{P(B)}, \tag{22}$$

   where A and B represent the classes and features, respectively. $P(A|B)$ signifies the conditional probability of class A, given the features within B. Conversely, $P(A)$ is the prior probability of event A and $P(B)$ signifies the probability of the comprehensive set of features, which is used as a normalization factor.
2) *K-nearest*
   In *K-nearest*, new data are classified based on the majority vote of their nearest neighbors. The distance function determines the distance between neighbors. Parameter K signifies the number of neighbors considered. Lower K values tend to yield less consistent outcomes, while higher K values increase stability, but might also lead to higher error rates. It can also be used to identify a subset of the group and implement a synchronization or consensus technique.
   Because *k-nearest* stores the complete training dataset, there is no explicit training process. Because there were no computing operations during this stage, the training time complexity was effectively zero or constant. The size of the dataset, quantity of features, and value of K affect the *k-nearest* prediction process. The process can be computed as

$$d(x, x_i) = \sqrt{\sum_{j=1}^{k} (x_j - x_{ij})^2}, \tag{23}$$

   where k represents the number of features, x_j is the j-th feature value of test point x, and x_{ij} is the j-th feature value of the i-th point in the training set.

3) PATH PROBABILITY PREDICTION

In the NOMA environment, to finely tune and optimize the intricate dynamics of aerial networks to achieve more efficient and robust performance, path probability prediction introduces potent tools for the analysis, optimization, and enhancement of NOMA performance within dynamic and complex aerial networks. This approach harnesses the predictive capabilities of anticipating and assessing the probability of signal paths, thereby enabling an understanding of the communication environment. The path probability prediction can be generated using two models: the stochastic geometry model and the Markov model, which is explained in this section.

1) Stochastic Geometry Model A new three-dimensional UAV framework for providing wireless services to randomly roaming NOMA users using probabilistic spatial models to analyze and optimize communication systems. Stochastic geometry helps model the spatial distribution of UAVs and ground users. The models incorporate realistic channel characteristics considering UAVs' heights, locations, and effects of the A2G communication channels. Factors such as path loss, shadowing, and multipath fading due to UAV movement were considered.
   Stochastic geometry models can aid in optimizing resource allocation strategies for NOMA-based communication in UAV networks. This involves deciding on UP, power allocation, and subchannel assignment, considering the spatial distribution of UAVs and users. In addition, it can optimize the spatial deployment of UAVs to maximize coverage and throughput by considering the benefits of NOMA in enhancing spectral efficiency. Thus, the probability can be expressed as,
   $$P_i^G = exp\left(-\frac{PL}{\gamma}\right), \tag{24}$$
   where P_i^G is the probability of the ith building in the ground's specular propagation path, incident path, reflection path, and Fresnel reflection zone. Then PL is the path loss calculated using the path loss model based on the channel condition, and γ is the SNR threshold.
2) Markov Model Markov chains are leveraged to predict the likelihood of different propagation paths or channel states between the UAV and the GS. The Markov chain assumes the Markov property, where the future state depends only on the present state and not on the past states. The transition probabilities between different channel states were determined based on historical data, channel measurements, or statistical models. By analyzing the current state and transition probabilities, the Markov model predicts the likelihood of future channel states as the UAV moves or the communication scenario evolves.
   Applying a Markov model to predict path probabilities in A2G communication for UAVs in NOMA scenarios enables proactive decision-making regarding resource allocation and transmission strategies based on anticipated channel conditions. This aids in controlling UAVs, accounts for the effect of wind disturbance on UAVs, avoids collisions and obstacles among UAVs, and tracks targets while evading threats [136]. As in [137], a Markov model was proposed to capture mobile characteristics in realistic scenarios.

B. USL TECHNIQUES

The USL is an ML paradigm in which models are trained on unlabeled data without explicit guidance or labeled outcomes. USL is an ML technique used to uncover patterns, structures, or relationships within data that lacks explicit labels or predetermined outcomes. USL is crucial for examining and comprehending raw data, offering valuable insights and preparation that can be applied across different domains, spanning from initial data exploration to crafting features.

In the context of UAV for NOMA, USL techniques can identify hidden structures and clusters at communication environment by enabling the autonomous discovery of patterns and relationships within the data without explicit guidance. These algorithms can autonomously detect and adapt to changing network conditions, thereby uncovering insights that may not be apparent through manual analysis. USL techniques lie in itheir ability to optimize network performance and adapt to dynamic conditions of UAVs in the NOMA environment autonomously and effectively.

The work in [86] proposed an innovative cooperative network scheme incorporating aBS integration within the satellite framework by efficiently combining unsupervised ML algorithms. Similarly, in [138], USL was developed to extract aBS data to model the features for the clustering process in NOMA-enabled aerial networks. USL can be used in other industries; for example, in [139], a system for classifying research articles that can group them into relevant groups. Data points that belong to the same cluster are assumed to belong to the same class. Consequently, one can determine whether two points are part of the same cluster based on how similar they are to one another and other points. The clustering result are shown in Fig. 11c.

1) K-MEANS CLUSTERING

K-means clustering relies on centroids, computed as means, to represent the cluster centers. These centroids marked the central points of each cluster. Initially, K data points were randomly chosen from the existing dataset to serve as the initial centers for K clusters. The obtained value helps assign a data point to the cluster with the shortest distance. As new data points join a cluster, the similarity within the cluster is enhanced by recalculating a new mean from objects already assigned to that cluster. This updated mean reassigns the data objects. This process is iterated until stability is reached. The sum of the square functions for the k-means algorithm is given by,

$$d = \sum_{j=1}^{m}(x_{ij} - c_{kj})^2, \tag{25}$$

where x_{ij} is the j-th data point of i-th cluster and c_{kj} is the centroid of the j-th cluster.

2) STOCHASTIC NEIGHBOR EMBEDDING

Stochastic Neighbor Embedding (SNE) is an ML method for reducing dimensions and understanding data patterns, and adopts a probabilistic method. It treats each data point as potentially connected to others with certain probabilities to maintain these probabilities in the embedding space. Distributions around each data point define the likelihood of the other points being neighbors. The SNE relies on Gaussian distributions for probabilities in both the original and embedding spaces, and t-distributed SNE (t-SNE) for combining Student-t and Gaussian distributions in these spaces [140].

t-SNE embedding is a model based on probability distributions that maps high-dimensional data to lower dimensions while maintaining the closeness of neighboring data points. This method aims to conserve the original data structure but does not emphasize the discriminatory aspects of the data [141].

However, embedding high-dimensional data into a lower dimensional space poses challenges in maintaining the proximity between all points. The Student's t-distribution utilizes the low dimensional embedding space, which features heavier tails compared to the Gaussian distribution, making it able to fit the accommodation of high-dimensional data information within a lower-dimensional embedding space. The similarity between data points i and j in high-dimensional space is computed using a Gaussian kernel or Student's t-distribution. In high-dimensional space, the conditional probability is calculated based on their similarity using a Gaussian kernel, which can be expressed as

$$p_{ij} = \frac{exp(-d_{ij})}{\sum_{k\neq i} exp(-d_{ij})}, \tag{26}$$

where,

$$d_{ij} = \frac{||x_i - x_j||^2}{2\sigma_i^2}. \tag{27}$$

For a pair of data points x_i and x_j in high-dimensional space, $||x_i - x_j||$ represents the Euclidean distance between x_i and x_j, and σ^2 is a bandwidth parameter that determines the width of the Gaussian distribution at point x_i. Similarly, in lower-dimensional space, the conditional probability is calculated based on a Student's t-distribution, which can be expressed as

$$q_{ij} = \frac{exp(-z_{ij})}{\sum_{k\neq i} exp(-z_{ij})}, \tag{28}$$

where,

$$d_{ij} = ||y_i - y_j||^2. \tag{29}$$

The distances between y_i and y_j represent the similarity between points,

SNE aims to reduce the disparity between the conditional probabilities p_{ij} in high-dimensional space and q_{ij} in lower-dimensional space. This is often accomplished using a cost function, such as Kullback-Leibler (KL) divergence, as follows,

$$C = \sum_i KL(P_i||Q_i) = \sum_i \sum_j p_{ij} log \frac{p_i j}{q_{ij}}, \tag{30}$$

where p_{ij} and q_{ij} are (26) and (28), respectively. The optimization process involves adjusting the positions of points y_i in the lower dimensional space to minimize the cost function C, usually through gradient descent or other iterative optimization techniques.

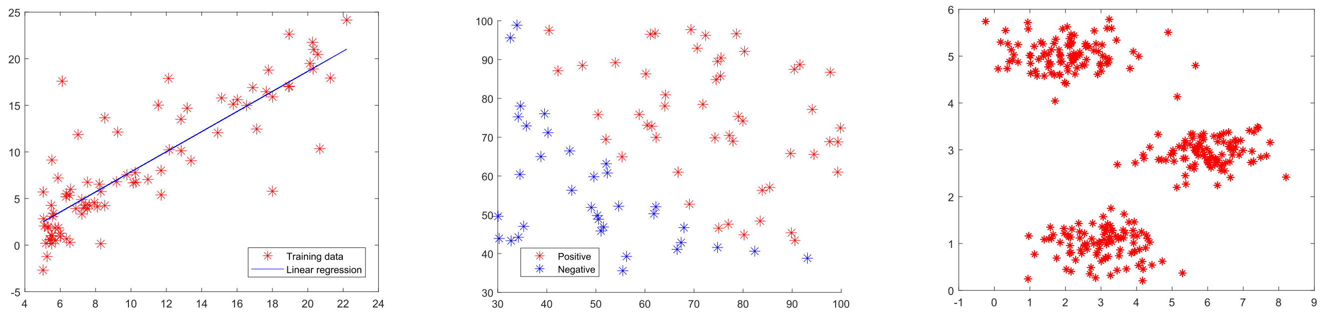
C. SSL TECHNIQUES

An ML algorithm that is between SL and USL is called SSL. The subfield of ML seeks to integrate these two objectives. Using this algorithm, the model improves the performance by learning from both labeled and unlabeled data. The SSL combines a small set of labeled data with a larger set of unlabeled data to train the models. The model aims to exploit the underlying structure or patterns of unlabeled data to improve its learning and generalization.

This approach combines the strengths of both SL and USL, making SSL utilize labeled data to train models on specific tasks such as resource allocation or interference management. Simultaneously, the model learns at broader set of unlabeled data to discover patterns and adapt to dynamic network conditions. By efficiently leveraging both types of data, SSL contributes to improved performance, adaptability, and robustness in UAV-NOMA communication systems.

The work of [142] utilized the MIMO-NOMA concept to enhance efficiency by employing a limited subset of existing labeled data generated through numerical iterative algorithms for training using SSL techniques. Meanwhile, in [143], the difficult issues of user grouping and power allocation problems in NOMA systems were addressed by invoking SSL to group users using consequent groupings. The work of [144] performs an approach for semi-supervised reconstruction that breaks down distorted image sequences into their basic components. SSL is primarily associated with pseudo-labelling. Pseudo-label techniques often use model predictions to assign labels to unlabeled data. This approach to improving current algorithms involves training classifiers initially using data. These classifiers then generate additional labeled data by leveraging their predictions. Recent studies have proven that pseudo-labelling is a simple yet effective approach for semi-supervised learning [145], [146], [147].

The iterative process comprises two fundamental steps: training and pseudo-labelling. In the training phase, one or more supervised classifiers undergo learning using labeled data, and can potentially incorporate pseudo-labelled data sourced from prior iterations. Subsequently, in the pseudo-labelling phase, these classifiers extrapolate labels to previously unlabeled instances. Specifically, this involves



(a) Regression (b) Classification (c) Clustering

FIGURE 11. ML models.

assigning labels to data points where classifiers exhibit the highest confidence in their predictions. These augmented pseudo-labelled datasets were subsequently integrated into the following iteration for further refinement and enhancement of the learning process.

Instead of repeatedly retraining the entire algorithm, pseudo-labelling occurred continuously during the training process. As the pseudo-labels generated earlier tend to be less dependable, their influence gradually strengthens over time. This pseudo-labelling method shares similarities with self training but diverges in the aspect that the classifier is not retrained after each pseudo-labelling step. Rather, it undergoes fine-tuning using fresh pseudo-labelled data, thus differing from the wrapper method paradigm in a technical sense.

The work of [148] proposes an approach that combines labeled and unlabeled data to create meaningful representations by expanding self-supervised contrastive learning, which is formed by distinguishing between two samples: whether they represent the same underlying data positive or negative. According to [148] pseudo-label, $\overline{y_j}$ can be computed as,

$$\overline{y_j} = mode_{y_s}(\tilde{z}^{a_2}_{s,t}, y_s)^{k}_{s=1}, \tag{31}$$

where mode is the mode of the set and obtains the most frequent class in the k-nearest neighbors.

D. RL TECHNIQUES

RL is an ML approach, in which an agent learns by interacting with an environment to achieve predefined objectives or goals. Unlike supervised or unsupervised learning, RL involves the learning from feedback received in the form of rewards or penalties as it navigates through this environment.

By enabling UAVs to learn optimal strategies through interactions with their environment, RL can be applied to enhance resource allocation, interference management, and decision-making processes. The UAV, acting as an agent, learns by receiving feedback from the environment, based on its actions. The continuous learning process of RL allows UAVs to make informed decisions in real-time. This adaptive capability is crucial for UAV-NOMA systems, particularly in scenarios with varying user demands, mobility patterns, and interference levels.

An agent that engages in the environment facing different states and possible actions. It is empowered to make decisions in this environment, receiving instant feedback after each action, indicating the quality of the action taken in a specific state. RL helps agents learn the best actions through trial and error, allowing them to adjust different environments to reach specific goals. This is used in many fields where learning from interactions and decision making matters.

Several studies have been conducted on RL applications in NOMA on aerial networks, in [149] an RL algorithm was applied to transform a UAV into a learning agent that serves an IoT area within the NOMA-UAV network to create a dynamic and responsive system for resource allocation in UAV networks. The work of [150] RL can be used as the UAV trajectory and power allocation design, whereas NOMA enhances the spectrum efficiency of the entire network, particularly in scenarios where UEs move randomly. In [151], RL was used for aerial data collection in NOMA-IoT networks by utilizing UAVs as remote terminals and NOMA to solve massive access problems.

At fundamental formula in reinforcement learning is the Q-learning algorithm, which updates the Q-values representing the expected cumulative future rewards for taking a specific action in a particular state. The Q-value for a state action pair $Q(s, a)$ is updated based on the observed reward r and the maximum Q-value of the next state s' considering all possible actions. Q-learning can be expressed as

$$Q(s, a) \leftarrow Q(s, a) + \alpha[r + \lambda \max_{a} Q(s', a') - Q(s, a)] \tag{32}$$

where $Q(s, a)$ and $max_a Q(s', a')$ denote the Q-value and maximum Q-value achievable for taking actions a and a' in states s and s'. Then, a denotes the learning rate and s' denotes the next state reached after taking action a. λ denotes the discount factor that balances immediate rewards against future rewards.

VII. FUTURE RESEARCH DIRECTION

In this section, we shed light on new opportunities in emerging network architectures and highlight interesting research topics for future research direction.

A. GRANT-FREE ACCESS

Grant-free NOMA is a communication technique used in wireless networks to allow multiple UEs to share the same frequency resources simultaneously without requiring a predefined allocation of time slots or resources (hence, ''grant-free''). Utilizing NOMA for grant-free access can enable more efficient and dynamic resource utilization, especially in scenarios involving multiple UEs or devices accessing shared communication channels simultaneously without requiring explicit grants for access. Grant-free NOMA is considered a promising technology for future wireless networks, including 5G and beyond, aiming to improve spectrum efficiency and accommodate diverse communication needs.

B. HARDWARE IMPAIRMENT

Owing to NOMA's inherent physical characteristics, RF transceivers are known to suffer from hardware impairments such as PA non-linearity, I/Q imbalance, and phase noise [152]. Hardware impairments in NOMA refer to various limitations or imperfections in the hardware components of a communication system that can affect the performance and reliability of NOMA-based communication systems. In NOMA, where multiple UEs' signals are superimposed, non-linearities can cause inter-modulation distortion, leading to signal degradation and reduced performance. Accurate signal reception is crucial for SIC in NOMA. Phase noise can disrupt the decoding process and reduce the SIC performance. However, a combination of advanced signal-processing techniques, improved hardware design, and innovative algorithms can mitigate the impact of hardware impairment, leading to enhanced performance and reliability in NOMA based communication systems.

C. HYBRID MULTIPLE ACCESS

NOMA relies on SC and SIC at the receiver to separate and decode multiple UEs' signals. However, owing to non-orthogonal links, accurately estimating each connection is challenging or even unfeasible. Consequently, this procedure may introduce interference, particularly when decoding signals with varying power levels. Consequently, the NOMA scheme may encounter limitations such as reduced capacity and higher error rates. To address this issue, a hybrid multiple access approach was devised with the aim of optimizing the overall throughput of the system. Hybrid multiple access refers to a communication method that combines different access techniques within the same network. The idea behind hybrid multiple access is to tailor the access method based on UEs' requirements, network conditions, and specific application scenarios. This adaptive approach seeks to improve the network capacity, enhance throughput, and efficiently manage diverse communication needs within a unified framework.

D. UAV FLIGHT CONTROL AND TRAJECTORY ML BASED

It is important to ensure that UAVs navigate optimally. Poor flight can disrupt resources and hinder adaptation, thereby affecting the reliability and effectiveness of aerial communication networks. Enhancing UAV-based communication networks in NOMA involves adjusting the UAV trajectory to achieve better connections and manage interference. Owing to advancements in ML, UAVs can significantly enhance network performance, even in complex scenarios, by moving independently.

For instance, techniques such as DRL [153] help UAVs distribute resources efficiently and reduce data losses. Additionally, neural networks [154] aid in controlling UAVs, predicting UE behaviors, optimizing flight paths and connections to make the network run smoother.

E. ADAPTIVE BEAMFORMING

Considering the difficulties of UAV on NOMA, there is a need for robust optimization methods to precisely address the beamforming issue and decrease the computational load [155]. Adaptive beamforming for UAVs in NOMA networks adapts to changing conditions and ensure consistent and reliable connectivity across a dynamic and diverse UE landscape. Utilizing ML for adaptive beamforming techniques can optimize signal transmission, direct beams toward the UEs, and dynamically adjust beam directions based on changing network conditions. By presenting a robust beamforming design considering imperfect CSI at the transmitter under the constraints of information receivers and total transmit power.

F. AUTOMATED ML

Automated Machine Learning (AutoML) represents a revolutionary approach for streamlining and enhancing the ML process. Its primary objective is to automate the end-to-end ML workflow, thereby significantly reducing the need for extensive manual involvement and domain-specific knowledge. The increasing popularity of AutoML solutions stems from their potential to make ML accessible to individuals without specialized expertise in the field. As AutoML techniques advance, they are expected to play a crucial role in democratizing ML, allowing a broader audience to harness their power for innovation across various domains. The key functionalities of AutoML include automatically selecting the most suitable ML model or algorithm for a given dataset and task, fine-tuning model hyperparameters to optimize performance without manual intervention, selecting or generating relevant features from raw data to enhance model performance, and constructing comprehensive ML pipelines that encompass data preprocessing, model selection, and evaluation. This approach holds great promise for simplifying and democratizing the application of ML, fostering innovation, and advancements in diverse industries.

G. SECURITY ENCHANCEMENT

The frequency of privacy attacks on UAVs has increased significantly, and their potential impacts can be immensely destructive. Consequently, various industries and standardization are actively investigating strategies to secure UAV systems and networks.

ML techniques fortify UAV-NOMA networks by anomaly detection and intrusion to ensure secure communication. This real-time detection minimizes damage from cyber-attacks, protects sensitive data, automates threat responses, and enhances the overall operational efficiency. The network behavior and flagging deviations or anomalies that deviate from the learned normal patterns are continuosly analyzed. Techniques such as USL (e.g., clustering) or SSL can be employed for anomaly detection without requiring labeled datasets.

Implementing ML-driven security in UAV-NOMA networks enhances resilience against emerging cyber threats, ensuring the integrity, confidentiality, and availability of communication while also preserving data privacy within the network. It is crucial to safeguard the critical operations and sensitive information transmitted over these networks.

H. FURTHER INTERESTING RESEARCH

Apart from the previously discussed topics, several unresolved issues remain concerning the practical implementation of UAV, NOMA, and ML. For instance, in UAV-based multi-UE NOMA systems, managing the high density of low-altitude UAV traffic requires the implementation of new unmanned aircraft traffic management systems [156]. These systems are crucial for coordinating path planning and preventing collisions between multiple UAVs. In multiple UAV systems, knowing the direction of incoming signals allows for better allocation of resources, such as power and bandwidth, to improve the overall efficiency of the communication system. Thus, estimation direction-of-arrival (DOA) is used to determine the angles from which signals arrive at an antenna array [157]. Furthermore, in NOMA systems, accurate estimation of the DOA using advanced ML is a robust future study. Utilizing a stacked intelligent metasurface (SIM) for extensive parallel computation and analog signal processing involves employing an array of programmable metasurface layers [158], [159].

With the advancement of ML, there is a growing need for enhanced privacy protection, particularly when analyzing personal and sensitive data. Consequently, it is essential to ensure that no analysis compromises individual privacy. To ensure the privacy of UAV communication and maintain data integrity, the emergence of blockchain technology, specifically aerial blockchains, is anticipated. This technology securely upholds privacy preference. Hence, software-defined multiple-access technology and ML are anticipated to facilitate the adaptable configuration of multiple-access schemes, accommodating diverse services and applications.

Integrating NOMA and ML in UAV communication encounters challenges such as dynamic resource allocation and demanding sophisticated models adapted to the unique characteristics of NOMA-enabled UAV network's. To address these challenges, there is a need for specific solutions such as exploring advanced algorithms for dynamic resource allocation, enhancing security and privacy measures, optimizing computational efficiency for UAVs with limited resources, and developing scalable approaches for large-scale UAV networks. Further investigation is crucial for proposing and implementing targeted solutions in each of these areas. Addressing security, privacy, computational complexity in resource-constrained UAVs, and scalability issues in large-scale networks are additional challenges that require careful consideration for achieving seamless integration. It is expected that constraints such as dynamic wireless channels, limited battery capacities, and computational resources of UAVs make traditional methods inefficient in UAV networks. Examining and proposing solutions to DOA concerns associated with multiple UAVs in NOMA networks, focusing on integrating SIM as computation and blockchain technology for enhanced data security and confidentiality.

Additionally, incorporating ML in NOMA-based UAV networks encompasses inherent limitations, particularly computational complexities. UAV communication environments are dynamic and unpredictable. The effectiveness of ML models often depends on the availability of diverse and representative training data. Obtaining such data for NOMA-based UAV-specific scenarios might be challenging. ML models trained on historical data may struggle to adapt to rapidly changing conditions, limiting their robustness.

To address these challenges, there is a need for specific solutions, such as exploring advanced algorithms for dynamic resource allocation, enhancing security and privacy measures, optimizing computational efficiency for UAVs with limited resources, and developing scalable approaches for large-scale UAV networks. Further investigation is crucial to propose and implement targeted solutions in each of these areas.

VIII. CONCLUSION

The increasing demand in various fields necessitates innovative solutions, and UAVs have gained research attention to address these needs. This study provides an introduction to UAVs, NOMA, and ML, along with key insights. To overcome these demands and utilize ML as a tool to support NOMA in aerial networks, NOMA is used. An overview of NOMA in aerial networks and each application that allows aerial networks are also provided. By adding ML as support, these three schemes form a comprehensive approach. These schemes are expected to play an important role as a starting point in the next wireless connectivity application.

REFERENCES

[1] N. Bloise, S. Primatesta, R. Antonini, G. P. Fici, M. Gaspardone, G. Guglieri, and A. Rizzo, "A survey of unmanned aircraft system technologies to enable safe operations in urban areas," in *Proc. Int. Conf. Unmanned Aircr. Syst. (ICUAS)*, Jun. 2019, pp. 433–442.

[2] H. Wang, J. Wang, G. Ding, L. Wang, T. A. Tsiftsis, and P. K. Sharma, "Resource allocation for energy harvesting-powered D2D communication underlaying UAV-assisted networks," *IEEE Trans. Green Commun. Netw.*, vol. 2, no. 1, pp. 14–24, Mar. 2018.

[3] X. Gu and G. Zhang, "A survey on uav-assisted wireless communication: Recent advances and future trends," *Comput. Commun.*, vol. 208, pp. 44–78, Jul. 2023.

[4] S. Hayat, E. Yanmaz, and R. Muzaffar, "Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 4, pp. 2624–2661, 4th Quart., 2016.

[5] X. Cao, P. Yang, M. Alzenad, D. Wu, and H. Yanikomeroglu, "Airbone communication networks: A survey," *IEEE J. Sel. Areas Communcation*, vol. 36, no. 9, pp. 1907–1926, Nov. 2018.

[6] A. F. M. S. Shah, A. N. Qasim, M. A. Karabulut, H. Ilhan, and M. B. Islam, "Survey and performance evaluation of multiple access schemes for next-generation wireless communication systems," *IEEE Access*, vol. 9, pp. 113428–113442, 2021.

[7] Y. Al-Eryani and E. Hossain, "The D-OMA method for massive multiple access in 6G: Performance, security, and challenges," *IEEE Veh. Technol. Mag.*, vol. 14, no. 3, pp. 92–99, Sep. 2019.

[8] A. A. Nasir, H. D. Tuan, T. Q. Duong, and H. V. Poor, "UAV-enabled communication using NOMA," *IEEE Trans. Commun.*, vol. 67, no. 7, pp. 5126–5138, Jul. 2019.

[9] R. Saravanan and P. Sujatha, "A state of art techniques on machine learning algorithms: A perspective of supervised learning approaches in data classification," in *Proc. 2nd Int. Conf. Intell. Comput. Control Syst. (ICICCS)*, Jun. 2018, pp. 945–949.

[10] H. Kour and N. Gondhi, *Machine Learning Techniques: A Survey*. Cham, Switzerland: Springer, 2020, pp. 266–275.

[11] S. A. R. Naqvi, S. A. Hassan, H. Pervaiz, and Q. Ni, "Drone-aided communication as a key enabler for 5G and resilient public safety networks," *IEEE Commun. Mag.*, vol. 56, no. 1, pp. 36–42, Jan. 2018.

[12] M. Agiwal, A. Roy, and N. Saxena, "Next generation 5G wireless networks: A comprehensive survey," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 3, pp. 1617–1655, 3rd Quart., 2016.

[13] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, and M. Debbah, "A tutorial on UAVs for wireless networks: Applications, challenges, and open problems," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2334–2360, 3rd Quart., 2019.

[14] C. Zhang, P. Patras, and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2224–2287, 3rd Quart., 2019.

[15] W. Jaafar, S. Naser, S. Muhaidat, P. C. Sofotasios, and H. Yanikomeroglu, "Multiple access in aerial networks: From orthogonal and non-orthogonal to rate-splitting," *IEEE Open J. Veh. Technol.*, vol. 1, pp. 372–392, 2020, doi: 10.1109/OJVT.2020.3032844.

[16] 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)*, Feb. 2020, pp. 303–307.

[17] M. B. Shahab, R. Abbas, M. Shirvanimoghaddam, and S. J. Johnson, "Grant-free non-orthogonal multiple access for IoT: A survey," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 3, pp. 1805–1838, 3rd Quart., 2020.

[18] W. Ahsan, W. Yi, Z. Qin, Y. Liu, and A. Nallanathan, "Resource allocation in uplink NOMA-IoT networks: A reinforcement-learning approach," *IEEE Trans. Wireless Commun.*, vol. 20, no. 8, pp. 5083–5098, Aug. 2021.

[19] M.-A. Lahmeri, M. A. Kishk, and M.-S. Alouini, "Artificial intelligence for UAV-enabled wireless networks: A survey," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 1015–1040, 2021.

[20] A. O. Hashesh, S. Hashima, R. M. Zaki, M. M. Fouda, K. Hatano, and A. S. T. Eldien, "AI-enabled UAV communications: Challenges and future directions," *IEEE Access*, vol. 10, pp. 92048–92066, 2022.

[21] U. Ghafoor, M. Ali, H. Z. Khan, A. M. Siddiqui, and M. Naeem, "NOMA and future 5G & B5G wireless networks: A paradigm," *J. Netw. Comput. Appl.*, vol. 204, Aug. 2022, Art. no. 103413.

[22] R. K. Senapati and P. J. Tanna, "Deep learning-based NOMA system for enhancement of 5G networks: A review," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 3, pp. 1–15, Sep. 2022.

[23] N. I. Sarkar and S. Gul, "Artificial intelligence-based autonomous UAV networks: A survey," *Drones*, vol. 7, no. 5, p. 322, May 2023.

[24] P. S. Bithas, E. T. Michailidis, N. Nomikos, D. Vouyioukas, and A. G. Kanatas, "A survey on machine-learning techniques for UAV-based communications," *Sensors*, vol. 19, no. 23, p. 5170, Nov. 2019.

[25] S. Sai, A. Garg, K. Jhawar, V. Chamola, and B. Sikdar, "A comprehensive survey on artificial intelligence for unmanned aerial vehicles," *IEEE Open J. Veh. Technol.*, vol. 4, pp. 713–738, 2023.

[26] T. Nithya, V. N. Kumar, G. S. S. Deepa, C. M. Varun, and R. S. Subramanian, "A comprehensive survey of machine learning: Advancements, applications, and challenges," in *Proc. 2nd Int. Conf. Augmented Intell. Sustain. Syst. (ICAISS)*, Aug. 2023, pp. 354–361.

[27] D. Mourtzis, J. Angelopoulos, and N. Panopoulos, "UAVs for industrial applications: Identifying challenges and opportunities from the implementation point of view," *Proc. Manuf.*, vol. 55, no. 11, pp. 183–190, Jan. 2021.

[28] K. Guo, M. Wu, X. Li, H. Song, and N. Kumar, "Deep reinforcement learning and NOMA-based multi-objective RIS-assisted IS-UAV-TNs: Trajectory optimization and beamforming design," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 9, pp. 1–14, Jul. 2023.

[29] V. V. Chetlur and H. S. Dhillon, "Downlink coverage analysis for a finite 3-D wireless network of unmanned aerial vehicles," *IEEE Trans. Commun.*, vol. 65, no. 10, pp. 4543–4558, Oct. 2017.

[30] Z. Meng, Y. Chen, M. Ding, and D. López-Pérez, "A new look at UAV channel modeling: A long tail of LoS probability," in *Proc. IEEE 30th Annu. Int. Symp. Pers., Indoor Mobile Radio Commun. (PIMRC)*, Sep. 2019, pp. 1–6.

[31] C. Xu, L. Xiang, J. An, C. Dong, S. Sugiura, R. G. Maunder, L.-L. Yang, and L. Hanzo, "OTFS-aided RIS-assisted SAGIN systems outperform their OFDM counterparts in doubly selective high-Doppler scenarios," *IEEE Internet Things J.*, vol. 10, no. 1, pp. 682–703, Jan. 2023.

[32] C. Xu, J. An, T. Bai, S. Sugiura, R. G. Maunder, Z. Wang, L.-L. Yang, and L. Hanzo, "Channel estimation for reconfigurable intelligent surface assisted high-mobility wireless systems," *IEEE Trans. Veh. Technol.*, vol. 72, no. 1, pp. 718–734, Jan. 2023.

[33] K. Venkateswararao, P. Kumar, A. Solanki, and P. Swain, "BandBlock: Bandwidth allocation in blockchain-empowered UAV-based heterogeneous networks," *ETRI J.*, vol. 44, no. 6, pp. 945–954, Dec. 2022.

[34] M. Mozaffari, A. Taleb Zadeh Kasgari, W. Saad, M. Bennis, and M. Debbah, "Beyond 5G with UAVs: Foundations of a 3D wireless cellular network," *IEEE Trans. Wireless Commun.*, vol. 18, no. 1, pp. 357–372, Jan. 2019.

[35] M. D. Nguyen, T. M. Ho, L. B. Le, and A. Girard, "UAV placement and bandwidth allocation for UAV based wireless networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2019, pp. 1–6.

[36] M. Horani and M. O. Hasna, "Latency analysis of UAV based communication networks," in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, Oct. 2018, pp. 385–390.

[37] J. Kakar and V. Marojevic, "Waveform and spectrum management for unmanned aerial systems beyond 2025," in *Proc. IEEE 28th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun. (PIMRC)*, Oct. 2017, pp. 1–5.

[38] S. Yang, Z. Zhang, J. Zhang, X. Chu, and J. Zhang, "Adaptive modulation for wobbling uav air-to-ground links in millimeter-wave bands," Apr. 2022, *arXiv:2204.06673v1*.

[39] A. Benjebbour, Y. Saito, Y. Kishiyama, A. Li, A. Harada, and T. Nakamura, "Concept and practical considerations of non-orthogonal multiple access (NOMA) for future radio access," in *Proc. Int. Symp. Intell. Signal Process. Commun. Syst.*, Nov. 2013, pp. 770–774.

[40] A. Anwar, B.-C. Seet, M. A. Hasan, and X. J. Li, "A survey on application of non-orthogonal multiple access to different wireless networks," *Electronics*, vol. 8, no. 11, p. 1355, Nov. 2019.

[41] J. Dai, K. Niu, and J. Lin, "Code-domain non-orthogonal multiple access for visible light communications," *IEEE Globecom Workshops*, pp. 1–6, May 2018.

[42] K. R. Patel and S. Dasrao Deshmukh, "2S (Superposition coding, successive interference cancellation) operations in NOMA technology for 5G networks: Review and implementation," in *Proc. IEEE 8th Int. Conf. Converg. Technol.*, Apr. 2023, pp. 1–6.

[43] 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.

[44] X. Chen, A. Benjebbour, Y. Lan, A. Li, and H. Jiang, "Impact of rank optimization on downlink non-orthogonal multiple access (NOMA) with SU-MIMO," in *Proc. IEEE Int. Conf. Commun. Syst.*, Nov. 2014, pp. 233–237.
[45] Q. C. Li, H. Niu, A. T. Papathanassiou, and G. Wu, "5G network capacity: Key elements and technologies," *IEEE Veh. Technol. Mag.*, vol. 9, no. 1, pp. 71–78, Mar. 2014.
[46] C. Ouyang, Y. Liu, and H. Yang, "Revealing the impact of SIC in NOMA-ISAC," *IEEE Wireless Commun. Lett.*, vol. 12, no. 10, pp. 1707–1711, Dec. 2023.
[47] M. Monemi, H. Tabassum, and R. Zahedi, "On the performance of non-orthogonal multiple access (NOMA): Terrestrial vs. Aerial networks," in *Proc. IEEE 8th Int. Conf. Commun. Netw. (ComNet)*, Oct. 2020, pp. 1–8.
[48] P. Botsinis, D. Alanis, C. Xu, Z. Babar, D. Chandra, S. X. Ng, and L. Hanzo, "Air-to-ground NOMA systems for the 'Internet-Above-the-Cloud,'" *IEEE Access*, vol. 6, pp. 47442–47460, 2018.
[49] C.-X. Wang, J. Huang, H. Wang, X. Gao, X. You, and Y. Hao, "6G wireless channel measurements and models: Trends and challenges," *IEEE Veh. Technol. Mag.*, vol. 15, no. 4, pp. 22–32, Dec. 2020.
[50] M. Pang, Q. Zhu, C.-X. Wang, Z. Lin, J. Liu, C. Lv, and Z. Li, "Geometry-based stochastic probability models for the LoS and NLoS paths of A2G channels under urban scenarios," *IEEE Internet Things J.*, vol. 10, no. 3, pp. 2360–2372, Feb. 2023.
[51] L. Dai, B. Wang, Z. Ding, Z. Wang, S. Chen, and L. Hanzo, "A survey of non-orthogonal multiple access for 5G," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 3, pp. 2294–2323, 3rd Quart., 2018.
[52] X. Li, J. Li, Y. Liu, Z. Ding, and A. Nallanathan, "Residual transceiver hardware impairments on cooperative NOMA networks," *IEEE Trans. Wireless Commun.*, vol. 19, no. 1, pp. 680–695, Jan. 2020.
[53] Q. Huang, W. Wang, W. Lu, N. Zhao, A. Nallanathan, and X. Wang, "Resource allocation for multi-cluster NOMA-UAV networks," *IEEE Trans. Commun.*, vol. 70, no. 12, pp. 8448–8459, Dec. 2022.
[54] Y. Zeng, R. Zhang, and T. J. Lim, "Throughput maximization for UAV-enabled mobile relaying systems," *IEEE Trans. Commun.*, vol. 64, no. 12, pp. 4983–4996, Dec. 2016.
[55] Q. Wu and R. Zhang, "Common throughput maximization in UAV-enabled OFDMA systems with delay consideration," *IEEE Trans. Commun.*, vol. 66, no. 12, pp. 6614–6627, Dec. 2018.
[56] S. Feng, T. Bai, and L. Hanzo, "Joint power allocation for the multi-user NOMA-downlink in a power-line-fed VLC network," *IEEE Trans. Veh. Technol.*, vol. 68, no. 5, pp. 5185–5190, May 2019.
[57] T. V. Tung, T. T. An, and B. M. Lee, "Joint resource and trajectory optimization for energy efficiency maximization in UAV-based networks," *Mathematics*, vol. 10, no. 20, p. 3840, Oct. 2022.
[58] M. Al-Imari, P. Xiao, M. A. Imran, and R. Tafazolli, "Uplink non-orthogonal multiple access for 5G wireless networks," in *Proc. 11th Int. Symp. Wireless Commun. Syst. (ISWCS)*, Aug. 2014, pp. 781–785.
[59] M. T. Nguyen and L. B. Le, "NOMA user pairing and UAV placement in UAV-based wireless networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2019, pp. 1–6.
[60] J. Wang, M. Liu, J. Sun, G. Gui, H. Gacanin, H. Sari, and F. Adachi, "Multiple unmanned-aerial-vehicles deployment and user pairing for nonorthogonal multiple access schemes," *IEEE Internet Things J.*, vol. 8, no. 3, pp. 1883–1895, Feb. 2021.
[61] Y. Yan, H. Xu, N. Zhang, G. Han, and M. Liu, "Dynamic divide grouping non-orthogonal multiple access in terrestrial-satellite integrated network," *Sensors*, vol. 21, no. 18, p. 6199, Sep. 2021.
[62] T. L. Nguyen, G. Kaddoum, T. N. Do, D. B. da Costa, and Z. J. Haas, "Adaptive decoding mechanisms for UAV-enabled double-uplink coordinated NOMA," *IEEE Trans. Veh. Technol.*, vol. 72, no. 8, pp. 1–17, Mar. 2023.
[63] K. Wang, T. Zhou, T. Xu, H. Hu, and X. Tao, "Asymmetric adaptive modulation for uplink NOMA systems," *IEEE Trans. Commun.*, vol. 69, no. 11, pp. 7222–7235, Nov. 2021.
[64] I. Bekmezci, M. Ermis, and S. Kaplan, "Connected multi UAV task planning for flying ad hoc networks," in *Proc. IEEE Int. Black Sea Conf. Commun. Netw.*, May 2014, pp. 28–32.
[65] V. Sharma and R. Kumar, "A cooperative network framework for multi-UAV guided ground ad hoc networks," *J. Intell. Robotic Syst.*, vol. 77, nos. 3–4, pp. 629–652, Mar. 2015.
[66] T. Kim, S. Lee, K. H. Kim, and Y.-I. Jo, "FANET routing protocol analysis for multi-UAV-based reconnaissance mobility models," *Drones*, vol. 7, no. 3, p. 161, Feb. 2023.
[67] M. Nauman Bashir, S. Iqbal, and K. Mohamad Yusof, "Design principles for cooperative relaying on UAVs-based FANET," in *Proc. Adv. Sci. Eng. Technol. Int. Conf. (ASET)*, Feb. 2022, pp. 1–6.
[68] X. Yang, B. Han, G. Zhang, P. Zheng, J. Bai, and D. Qin, "NOMA-assisted routing algorithm design for UAV ad hoc relay networks," *IEEE Sensors J.*, vol. 23, no. 3, pp. 3296–3312, Feb. 2023.
[69] N. Nomikos, A. Giannopoulos, A. Kalafatelis, V. Özduran, P. Trakadas, and G. K. Karagiannidis, "Improving connectivity in 6G maritime communication networks with UAV swarms," *IEEE Access*, vol. 12, pp. 18739–18751, 2024.
[70] Y. Liu, Z. Qin, Y. Cai, Y. Gao, G. Y. Li, and A. Nallanathan, "UAV communications based on non-orthogonal multiple access," *IEEE Wireless Commun.*, vol. 26, no. 1, pp. 52–57, Feb. 2019.
[71] S. Zhang, Y. Zeng, and R. Zhang, "Cellular-enabled UAV communication: A connectivity-constrained trajectory optimization perspective," *IEEE Trans. Commun.*, vol. 67, no. 3, pp. 2580–2604, Mar. 2019.
[72] R. Tang, R. Zhang, Y. Xu, and J. He, "Energy-efficient optimization algorithm in NOMA-based UAV-assisted data collection systems," *IEEE Wireless Commun. Lett.*, vol. 12, no. 1, pp. 158–162, Jan. 2023.
[73] B. Li, Z. Fei, and Y. Zhang, "UAV communications for 5G and beyond: Recent advances and future trends," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2241–2263, Apr. 2019.
[74] Y. Liu, S. Zhang, X. Mu, Z. Ding, R. Schober, N. Al-Dhahir, E. Hossain, and X. Shen, "Evolution of NOMA toward next generation multiple access (NGMA) for 6G," *IEEE J. Sel. Areas Commun.*, vol. 40, no. 4, pp. 1037–1071, Apr. 2022.
[75] N. Nomikos, A. Giannopoulos, P. Trakadas, and G. K. Karagiannidis, "Uplink NOMA for UAV-aided maritime Internet-of-Things," in *Proc. 19th Int. Conf. Design Reliable Commun. Netw. (DRCN)*, Apr. 2023, pp. 1–6.
[76] J. Baek, S. I. Han, and Y. Han, "Optimal resource allocation for non-orthogonal transmission in UAV relay systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 3, pp. 356–359, Jun. 2018.
[77] S. K. Zaidi, S. F. Hasan, X. Gui, N. Siddique, and S. Ahmad, "Exploiting UAV as NOMA based relay for coverage extension," in *Proc. 2nd Int. Conf. Comput. Appl. Inf. Secur. (ICCAIS)*, May 2019, pp. 1–5.
[78] X. Jiang, Z. Wu, Z. Yin, Z. Yang, and N. Zhao, "Power consumption minimization of UAV relay in NOMA networks," *IEEE Wireless Commun. Lett.*, vol. 9, no. 5, pp. 666–670, May 2020.
[79] D. Zhai, H. Li, X. Tang, R. Zhang, Z. Ding, and F. R. Yu, "Height optimization and resource allocation for NOMA enhanced UAV-aided relay networks," *IEEE Trans. Commun.*, vol. 69, no. 2, pp. 962–975, Feb. 2021.
[80] J. Men, J. Ge, and C. Zhang, "Performance analysis of nonorthogonal multiple access for relaying networks over Nakagami-*m* fading channels," *IEEE Trans. Veh. Technol.*, vol. 66, no. 2, pp. 1200–1208, Feb. 2017.
[81] L. Tsipi, M. Karavolos, P. Bithas, and D. Vouyioukas, "Machine learning-based methods for enhancement of UAV-NOMA and D2D cooperative networks," *Sensors*, vol. 23, no. 6, p. 3014, Mar. 2023.
[82] V. N. Vo, L.-M.-D. Nguyen, H. Tran, V.-H. Dang, D. Niyato, D. N. Cuong, N. C. Luong, and C. So-In, "Outage probability minimization in secure NOMA cognitive radio systems with UAV relay: A machine learning approach," *IEEE Trans. Cognit. Commun. Netw.*, vol. 9, no. 2, pp. 435–451, Apr. 2023.
[83] M. Erdelj and E. Natalizio, "UAV-assisted disaster management: Applications and open issues," in *Proc. Int. Conf. Comput., Netw. Commun. (ICNC)*, Feb. 2016, pp. 1–5.
[84] A. Merwaday, A. Tuncer, A. Kumbhar, and I. Guvenc, "Improved throughput coverage in natural disasters: Unmanned aerial base stations for public-safety communications," *IEEE Veh. Technol. Mag.*, vol. 11, no. 4, pp. 53–60, Dec. 2016.
[85] E. Montero, D. Rosário, and A. Santos, "Clustering users for the deployment of UAV as base station to improve the quality of the data," in *Proc. IEEE Latin-Amer. Conf. Commun. (LATINCOM)*, Nov. 2019, pp. 1–6.
[86] M. Karavolos, L. Tsipi, P. S. Bithas, D. Vouyioukas, and P. T. Mathiopoulos, "Satellite aerial terrestrial hybrid NOMA scheme in 6G networks: An unsupervised learning approach," in *Proc. 1st Int. Conf. 6G Netw. (6GNet)*, Jul. 2022, pp. 1–5.
[87] N. Senadhira, S. Durrani, X. Zhou, N. Yang, and M. Ding, "Impact of UAV trajectory on NOMA-assisted cellular-connected UAV networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2020, pp. 1–7.

[88] M. M. El-Gayar and M. N. Ajour, "Resource allocation in UAV-enabled NOMA networks for enhanced Six-G communications systems," *Electronics*, vol. 12, no. 24, p. 5033, Dec. 2023.
[89] F. Guo, L. Lu, Z. Zang, and M. Shikh-Bahaei, "Machine learning for predictive deployment of UAVs with multiple access," *IEEE Open J. Commun. Soc.*, vol. 4, pp. 908–921, 2023.
[90] F. Moreno-Cruz, V. Toral-López, M. R. Cuevas, J. F. Salmerón, A. Rivadeneyra, and D. P. Morales, "Dual-band store-and-use system for RF energy harvesting with off-the-shelf DC–DC converters," *IEEE Internet Things J.*, vol. 8, no. 5, pp. 3678–3688, Mar. 2021.
[91] E. Jayabalan and R. Pugazendi, "An efficient routing protocol for wireless body sensor networks using reinforced learning algorithm in clusters," *Meas., Sensors*, vol. 27, Jun. 2023, Art. no. 100730.
[92] M. A. Halimi, T. Khan, A. A. Kishk, and Y. M. M. Antar, "Rectifier circuits for RF energy harvesting and wireless power transfer applications: A comprehensive review based on operating conditions," *IEEE Microwave Mag.*, vol. 24, no. 1, pp. 46–61, Jan. 2023.
[93] Z. Yang, W. Xu, and M. Shikh-Bahaei, "Energy efficient UAV communication with energy harvesting," *IEEE Trans. Veh. Technol.*, vol. 69, no. 2, pp. 1913–1927, Feb. 2020.
[94] H. T. Duong, N. Nhat-Tien, T. N. Xuan, T. H. Nguyen, V. M. Bui, and N. N. Tan, "Uplink and downlink of energy harvesting noma system: Performance analysis," *J. Inf. Telecommun.*, vol. 8, no. 1, pp. 1–16, Jan. 2023.
[95] H. Al-Obiedollah, K. Cumanan, A. G. Burr, J. Tang, Y. Rahulamathavan, Z. Ding, and O. A. Dobre, "On energy harvesting of hybrid TDMA-NOMA systems," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2019, pp. 1–6.
[96] A.-N. Nguyen, V. N. Vo, C. So-In, and D.-B. Ha, "System performance analysis for an energy harvesting IoT system using a DF/AF UAV-enabled relay with downlink NOMA under Nakagami-*m* fading," *Sensors*, vol. 21, no. 1, p. 285, Jan. 2021.
[97] D.-T. Do, A.-T. Le, Y. Liu, and A. Jamalipour, "User grouping and energy harvesting in UAV-NOMA system with AF/DF relaying," *IEEE Trans. Veh. Technol.*, vol. 70, no. 11, pp. 11855–11868, Nov. 2021.
[98] K. K. Nguyen, N. A. Vien, L. D. Nguyen, M.-T. Le, L. Hanzo, and T. Q. Duong, "Real-time energy harvesting aided scheduling in UAV-assisted D2D networks relying on deep reinforcement learning," *IEEE Access*, vol. 9, pp. 3638–3648, 2021.
[99] A.-N. Nguyen, D.-B. Ha, V. N. Vo, V.-T. Truong, D.-T. Do, and C. So-In, "Performance analysis and optimization for IoT mobile edge computing networks with RF energy harvesting and UAV relaying," *IEEE Access*, vol. 10, pp. 21526–21540, 2022.
[100] R. Kumar, C. Kumar Singh, P. Kumar Upadhyay, A. M. Salhab, A. Arshad Nasir, and M. Masood, "IoT-inspired cooperative spectrum sharing with energy harvesting in UAV-assisted NOMA networks: Deep learning assessment," *IEEE Internet Things J.*, vol. 10, no. 24, pp. 22182–22196, Sep. 2023.
[101] Y. Yin, M. Liu, G. Gui, H. Gacanin, and H. Sari, "Minimizing delay for MIMO-NOMA resource allocation in UAV-assisted caching networks," *IEEE Trans. Veh. Technol.*, vol. 72, no. 4, pp. 4728–4732, Apr. 2023.
[102] N. Rao Kota and K. Naidu, "UAV assisted MIMO-NOMA for maximizing the sum capacity by satisfying the QoS of the users," in *Proc. IEEE Int. Symp. Smart Electron. Syst. (iSES)*, Dec. 2022, pp. 483–486.
[103] T. Hou, Y. Liu, Z. Song, X. Sun, and Y. Chen, "Multiple antenna aided NOMA in UAV networks: A stochastic geometry approach," *IEEE Trans. Commun.*, vol. 67, no. 2, pp. 1031–1044, Feb. 2019.
[104] X. Li, M. Zhang, H. Chen, C. Han, L. Li, D.-T. Do, S. Mumtaz, and A. Nallanathan, "UAV-enabled multi-pair massive MIMO-NOMA relay systems with low-resolution ADCs/DACs," *IEEE Trans. Veh. Technol.*, vol. 73, no. 2, pp. 2171–2186, Feb. 2024.
[105] B. M. Lee, "Enhancing IoT connectivity in massive MIMO networks through systematic scheduling and power control strategies," *Mathematics*, vol. 11, no. 13, p. 3012, Jul. 2023.
[106] B. M. Lee and H. Yang, "Blocking probability of massive MIMO: What is the capacity of a massive MIMO IoT system?" *J. Franklin Inst.*, vol. 360, no. 8, pp. 5354–5374, May 2023.
[107] B. M. Lee, "Energy efficient selected mapping schemes based on antenna grouping for industrial massive MIMO-OFDM antenna systems," *IEEE Trans. Ind. Informat.*, vol. 14, no. 11, pp. 4804–4814, Nov. 2018.
[108] M. Jafri, S. Srivastava, N. K. D. Venkategowda, A. K. Jagannatham, and L. Hanzo, "Cooperative hybrid transmit beamforming in cell-free mmWave MIMO networks," *IEEE Trans. Veh. Technol.*, vol. 72, no. 5, pp. 6023–6038, May 2023.
[109] H. Nosrati, E. Aboutanios, X. Wang, and D. Smith, "Switch-based hybrid beamforming for massive mimo communications in mmWave bands," *Signal Process.*, vol. 200, Jun. 2022, Art. no. 108659.
[110] M. K. Chary, C. V. Krishna, and D. R. Krishna, "Accurate channel estimation and hybrid beamforming using artificial intelligence for massive mimo 5G systems," *AEU Int. J. Electron. Commun.*, vol. 173, Oct. 2024, Art. no. 154971.
[111] H. Gao, C. Jia, W. Xu, C. Yuen, Z. Feng, and Y. Lu, "Machine learning-empowered beam management for mmWave-NOMA in multi-UAVs networks," *IEEE Trans. Veh. Technol.*, vol. 71, no. 8, pp. 8487–8502, Aug. 2022.
[112] M. Jia, Q. Gao, Q. Guo, and X. Gu, "Energy-efficiency power allocation design for UAV-assisted spatial NOMA," *IEEE Internet Things J.*, vol. 8, no. 20, pp. 15205–15215, Oct. 2021.
[113] A. Misra, M. P. Sarma, K. K. Sarma, and N. Mastorakis, "Temporal deep learning assisted UAV communication channel model for application in EH-MIMO-NOMA set-up," *J. Commun. Netw.*, vol. 24, no. 2, pp. 166–183, Apr. 2022.
[114] N. Nouri, F. Fazel, J. Abouei, and K. N. Plataniotis, "Multi-UAV placement and user association in uplink MIMO ultra-dense wireless networks," *IEEE Trans. Mobile Comput.*, vol. 22, no. 3, pp. 1615–1632, Mar. 2023.
[115] Y. Liu, H. Xing, C. Pan, A. Nallanathan, M. Elkashlan, and L. Hanzo, "Multiple-Antenna-Assisted non-orthogonal multiple access," *IEEE Wireless Commun.*, vol. 25, no. 2, pp. 17–23, Apr. 2018.
[116] K. B. Letaief, W. Chen, Y. Shi, J. Zhang, and Y. A. Zhang, "The roadmap to 6G: AI empowered wireless networks," *IEEE Commun. Mag.*, vol. 57, no. 8, pp. 84–90, Aug. 2019.
[117] Z. Han, B. Liu, S.-B. Lin, and D.-X. Zhou, "Deep convolutional neural networks with zero-padding: Feature extraction and learning," 2023, *arXiv:2307.16203*.
[118] F. Shaheen, B. Verma, and M. Asafuddoula, "Impact of automatic feature extraction in deep learning architecture," in *Proc. Int. Conf. Digit. Image Comput., Techn. Appl. (DICTA)*, Nov. 2016, pp. 1–8.
[119] Y. Lei, B. Yang, X. Jiang, F. Jia, N. Li, and A. K. Nandi, "Applications of machine learning to machine fault diagnosis: A review and roadmap," *Mech. Syst. Signal Process.*, vol. 138, Apr. 2020, Art. no. 106587.
[120] D. I. R. Rai, M. K. Tiwari, and A. Dolgui, "Machine learning in manufacturing and industry 4.0 applications," *Int. J. Prod. Res.*, vol. 59, no. 16, pp. 4773–4778, 2021.
[121] A. Stetco, F. Dinmohammadi, X. Zhao, V. Robu, D. Flynn, M. Barnes, J. Keane, and G. Nenadic, "Machine learning methods for wind turbine condition monitoring: A review," *Renew. Energy*, vol. 133, pp. 620–635, Apr. 2019.
[122] X. Dai and Z. Gao, "From model, signal to knowledge: A data-driven perspective of fault detection and diagnosis," *IEEE Trans. Ind. Informat.*, vol. 9, no. 4, pp. 2226–2238, Nov. 2013.
[123] W. Xu, J. An, Y. Xu, C. Huang, L. Gan, and C. Yuen, "Time-varying channel prediction for RIS-assisted MU-MISO networks via deep learning," *IEEE Trans. Cognit. Commun. Netw.*, vol. 8, no. 4, pp. 1802–1815, Dec. 2022.
[124] 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," *IEEE Wireless Commun. Lett.*, vol. 11, no. 7, pp. 1493–1497, Jul. 2022.
[125] A. O. Hashesh, A. S. Tag Eldien, M. M. Fouda, and R. M. Zaki, "AI-aided height optimization for NOMA-UAV networks," in *Proc. Int. Conf. Comput. Sci., Inf. Technol. Eng.*, Feb. 2023, pp. 843–846.
[126] M. Davari, N. Asadi, S. Mudur, R. Aljundi, and E. Belilovsky, "Probing representation forgetting in supervised and unsupervised continual learning," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2022, pp. 16691–16700.
[127] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller, "Playing Atari with deep reinforcement learning," 2013, *arXiv:1312.5602*.
[128] Y. Li, "Deep reinforcement learning: An overview," 2017, *arXiv:1701.07274*.
[129] S. Chowdhury and M. P. Schoen, "Research paper classification using supervised machine learning techniques," in *Proc. Intermountain Eng., Technol. Comput. (IETC)*, Oct. 2020, pp. 1–6.
[130] E. Dritsas, S. Alexiou, and K. Moustakas, "Cardiovascular disease risk prediction with supervised machine learning techniques," in *Proc. 8th Int. Conf. Inf. Commun. Technol. Ageing Well E-Health*, 2022, pp. 315–321.

[131] B. Noori, "Classification of customer reviews using machine learning algorithms," *Appl. Artif. Intell.*, vol. 35, no. 8, pp. 567–588, Jul. 2021.

[132] E. E. Abdallah, W. Eleisah, and A. F. Otoom, "Intrusion detection systems using supervised machine learning techniques: A survey," in *Proc. 13th Int. Conf. Ambient Syst. Netw. Technol.*, vol. 201, 2022, pp. 205–212.

[133] O. Iqbal Bajwa, H. Awais Baluch, and H. Aftab Saeed, "Machine learning techniques for predicting UAV design parameters: Overview, methodology and potential benefits," in *Proc. 19th Int. Bhurban Conf. Appl. Sci. Technol. (IBCAST)*, Aug. 2022, pp. 249–255.

[134] R. Martínez-Clark, J. Pliego-Jimenez, J. F. Flores-Resendiz, and D. Avilés-Velázquez, "Optimum k-Nearest neighbors for heading synchronization on a swarm of UAVs under a time-evolving communication network," *Entropy*, vol. 25, no. 6, p. 853, May 2023.

[135] B. Galkin, R. Amer, E. Fonseca, and L. A. DaSilva, "Intelligent base station association for UAV cellular users: A supervised learning approach," in *Proc. IEEE 3rd 5G World Forum (5GWF)*, Sep. 2020, pp. 383–388.

[136] S. Ragi and E. K. P. Chong, "UAV path planning in a dynamic environment via partially observable Markov decision process," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 49, no. 4, pp. 2397–2412, Oct. 2013.

[137] Y. Li, W. Wang, H. Gao, Y. Wu, M. Su, J. Wang, and Y. Liu, "Air-to-ground 3D channel modeling for UAV based on Gauss-Markov mobile model," *AEU Int. J. Electron. Commun.*, vol. 114, Feb. 2020, Art. no. 152995.

[138] J. Cui, M. B. Khan, Y. Deng, Z. Ding, and A. NaIlanathan, "Unsupervised learning approaches for user clustering in NOMA enabled aerial SWIPT networks," in *Proc. IEEE 20th Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Jul. 2019, pp. 1–5.

[139] S.-W. Kim and J.-M. Gil, "Research paper classification systems based on TF-IDF and LDA schemes," *Hum.-Centric Comput. Inf. Sci.*, vol. 9, no. 1, pp. 1–13, Dec. 2019.

[140] B. Ghojogh, A. Ghodsi, F. Karray, and M. Crowley, "Stochastic neighbor embedding with Gaussian and student-t distributions: Tutorial and survey," 2020, *arXiv:2009.10301*.

[141] J. Wang, H. Zhao, Y. Zhang, H. Wang, and J. Guo, "Unsupervised ensemble learning improves discriminability of stochastic neighbor embedding," *Int. J. Comput. Intell. Syst.*, vol. 16, no. 1, pp. 1–11, Mar. 2023.

[142] S. Devipriya, J. Martin Leo Manickam, and B. Victoria Jancee, "Energy-efficient semi-supervised learning framework for subchannel allocation in non-orthogonal multiple access systems," *ETRI J.*, vol. 45, no. 6, pp. 963–973, Dec. 2023.

[143] R. O. Omslandseter, L. Jiao, Y. Liu, and B. John Oommen, "User grouping and power allocation in NOMA systems: A novel semi-supervised reinforcement learning-based solution," *Pattern Anal. Appl.*, vol. 26, no. 1, pp. 1–17, Feb. 2023.

[144] B. Meinardus, M. Trzeciakiewicz, T. Herzig, M. Kwiatkowski, S. Matern, and O. Hellwich, "Decomposer: Semi-supervised learning of image restoration and image decomposition," 2023, *arXiv:2311.16829*.

[145] S. Li, Z. Wei, J. Zhang, and L. Xiao, "Pseudo-label selection for deep semi-supervised learning," in *Proc. IEEE Int. Conf. Prog. Informat. Comput. (PIC)*, Dec. 2020, pp. 1–5.

[146] D.-H. Lee, "Pseudo-label : The simple and efficient semi-supervised learning method for deep neural networks," in *Proc. Workshop, Challenges Represent. Learn. (WREPL)*, 2013, pp. 1–18.

[147] Y. He, W. Chen, K. Liang, Y. Tan, Z. Liang, and Y. Guo, "Pseudo-label correction and learning for semi-supervised object detection," 2023, *arXiv:2303.02998*.

[148] M. Bošnjak, P. H. Richemond, N. Tomasev, F. Strub, J. C. Walker, F. Hill, L. Holger Buesing, R. Pascanu, C. Blundell, and J. Mitrovic, "SemPPL: Predicting pseudo-labels for better contrastive representations," 2023, *arXiv:2301.05158*.

[149] S. K. Mahmud, Y. Liu, Y. Chen, and K. K. Chai, "Adaptive reinforcement learning framework for NOMA-UAV networks," *IEEE Commun. Lett.*, vol. 25, no. 9, pp. 2943–2947, Sep. 2021.

[150] P. Chen, J. Zhao, and F. Shen, "Deep reinforcement learning assisted UAV trajectory and resource optimization for NOMA networks," in *Proc. 14th Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Nov. 2022, pp. 933–938.

[151] Z. Zhang, C. Xu, Z. Li, X. Zhao, and R. Wu, "Deep reinforcement learning for aerial data collection in hybrid-powered NOMA-IoT networks," *IEEE Internet Things J.*, vol. 10, no. 2, pp. 1761–1774, Jan. 2023.

[152] E. Björnson, J. Hoydis, M. Kountouris, and M. Debbah, "Massive MIMO systems with non-ideal hardware: Energy efficiency, estimation, and capacity limits," *IEEE Trans. Inf. Theory*, vol. 60, no. 11, pp. 7112–7139, Nov. 2014.

[153] K. Li, W. Ni, and F. Dressler, "LSTM-characterized deep reinforcement learning for continuous flight control and resource allocation in UAV-assisted sensor network," *IEEE Internet Things J.*, vol. 9, no. 6, pp. 4179–4189, Mar. 2022.

[154] K. Li, W. Ni, Y. Emami, and F. Dressler, "Data-driven flight control of Internet-of-Drones for sensor data aggregation using multi-agent deep reinforcement learning," *IEEE Wireless Commun.*, vol. 29, no. 4, pp. 18–23, Aug. 2022.

[155] H. A. Kassir, Z. D. Zaharis, P. I. Lazaridis, N. V. Kantartzis, T. V. Yioultsis, and T. D. Xenos, "A review of the state of the art and future challenges of deep learning-based beamforming," *IEEE Access*, vol. 10, pp. 80869–80882, 2022.

[156] G. Yang, X. Lin, Y. Li, H. Cui, M. Xu, D. Wu, H. Rydén, and S. Bin Redhwan, "A telecom perspective on the Internet of Drones: From LTE-advanced to 5G," 2018, *arXiv:1803.11048*.

[157] J. An, C. Yuen, M. Di Renzo, M. Debbah, H. Vincent Poor, and L. Hanzo, "Stacked intelligent metasurface performs a 2D DFT in the wave domain for DOA estimation," 2023, *arXiv:2310.09861*.

[158] J. An, C. Xu, Q. Wu, D. W. K. Ng, M. D. Renzo, C. Yuen, and L. Hanzo, "Codebook-based solutions for reconfigurable intelligent surfaces and their open challenges," *IEEE Wireless Commun.*, early access, pp. 1–8, Nov. 2022, doi: 10.1109/MWC.010.2200312.

[159] J. An, C. Yuen, C. Xu, H. Li, D. Wing Kwan Ng, M. Di Renzo, M. Debbah, and L. Hanzo, "Stacked intelligent metasurface-aided MIMO transceiver design," 2023, *arXiv:2311.09814*.

MEYRA CHUSNA MAYARAKACA received the B.S. degree in telecommunication engineering from the Electronics Engineering Polytechnic Institute of Surabaya, Indonesia, in 2023. She is currently pursuing the M.S. degree with the Department of Intelligent Mechatronics Engineering, Sejong University, Seoul, South Korea. Her research interest includes wireless communications.

BYUNG MOO LEE (Senior Member, IEEE) received the Ph.D. degree in electrical and computer engineering from the University of California at Irvine, Irvine, CA, USA, in 2006.

He is currently an Associate Professor with the Department of Intelligent Mechatronics Engineering, Sejong University, Seoul, South Korea. Prior to joining Sejong University, he had ten years of industry experience, including research positions with the Samsung Electronics Seoul Research and Development Center, the Samsung Advanced Institute of Technology (SAIT), and Korea Telecom (KT) Research and Development Center. During his industry experience, he participated in IEEE 802.16/11, Wi-Fi Alliance, and 3GPP LTE standardizations, and also participated in Mobile VCE and Green Touch Research Consortiums, where he made numerous contributions and filed a number of related patents. His research interests include wireless communications, signal processing, and machine learning applications. He was the Vice Chairperson of the Wi-Fi Alliance Display MTG, from 2015 to 2016.