Generative AI-Powered Aerial Access Networks: Recent Studies and Future Outlook

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***Abstract*—Aerial access networks (AANs), comprising unmanned aerial vehicles (UAV), high-altitude platforms (HAPs), and low-earth orbit (LEO) satellites, are rapidly emerging as a critical component of next-generation communication systems. Their dynamic nature, heterogeneous composition, and vast coverage area pose significant challenges for network management and optimization. Generative artificial intelligence (GenAI), renowned for its ability to generate new content, offers a promising solution to these challenges. In this paper, we explore the applications of GenAI in AANs in recent studies. We also identify key challenges and outline promising research directions.**

***Index Terms*—aerial access network, generative AI, recent studies, future outlook.**

I. Introduction

Mobile networks are rapidly evolving from 5G to 6G, with each generation offering significant improvements. Although 5G has already made a positive impact, the full potential of 5G can only be realized through the development of 5G-Advanced systems [1]. Simultaneously, research into the next-generation 6G technology is underway, exploring uncharted territories to meet future Internet of Things (IoT) demands. Central to the vision of a unified 6G network infrastructure is the integration of non-terrestrial components. Aerial access networks (AANs) have emerged as a viable technology to address the growing need for high-speed, ubiquitous connectivity [2]. By offering rapid deployment, extended coverage, and improved resilience, AANs complement traditional terrestrial networks, particularly in challenging environments such as disaster-prone areas. To fully leverage the capabilities of AANs in 5G-Advanced and 6G, overcoming challenges related to their dynamic topology, heterogeneous nature, and resource constraints is crucial. Intelligent solutions are essential for the efficient operation of these networks [2], [3].

Reinforcement learning (RL) emerges as a promising paradigm for constructing intelligent control mechanisms within AANs [3]–[6]. RL agents, through their interactions with the environment and the receipt of rewards, are capable of learning to make optimal decisions in complex and dynamic settings. However, RL agents typically require a substantial number of training episodes to converge to optimal policies, posing a significant challenge for AANs. The acquisition of large-scale real-world training datasets is often arduous, and RL algorithms frequently suffer from sample inefficiency, hindering their application in AAN environments. Recently, the convergence of cutting-edge technologies, including transformer architectures, deep learning algorithms, and Graphics Processing Units (GPUs)-accelerated computing, has fueled the rapid growth of generative artificial intelligence (GenAI) [7]. This technological convergence has led to the development of highly capable GenAI models, especially Large Language Models (LLMs) [8], including the renowned generative pre-trained transformers (GPTs). The impressive performance of GenAI models (e.g., OpenAI's GPT-4) and their accessibility through user-friendly interfaces have made text and image generation a common part of everyday life. GenAI is now revolutionizing various industries and emerging applications, transforming the world around us.

Motivated by the immense potential of GenAI, recent research has explored its application in the wireless communication domain. For instance, the study [9] explored large AI models in 6G, covering their potential, challenges, and future prospects. The work [10] investigated how large GenAI models can be utilized for designing, configuring, and operating wireless networks. The paper [11] explored the potential of UAVs in enhancing mission-critical networks and also introduced GenAI as a promising solution for future UAV-assisted systems. In [8], the authors examined the substantial benefits of leveraging UAV-LLM integration for the advancement of autonomous systems. By integrating GenAI into AANs, network operators can optimize network performance, improve resource utilization, and facilitate intelligent decision-making. This paper offers a survey of the current research on GenAI-powered AANs, emphasizing key contributions and identifying promising avenues for future exploration.

II. Aerial Access Networks

Before delving into the role of GenAI, it is essential to understand the AANs and their challenges. As illustrated in Fig. 1, AANs, employing aerial platforms such as UAVs, HAPs, and satellites, can offer a cutting-edge solution to meet the increasing demand for high-speed, reliable connectivity, especially in remote or disaster-struck regions [2], [3]. UAVs operate at various altitudes, from hundreds to thousands of meters, covering several kilometers. They are easy to use, deploy, and move. They can form networks and relay signals. However, limited battery life restricts their operation to tens

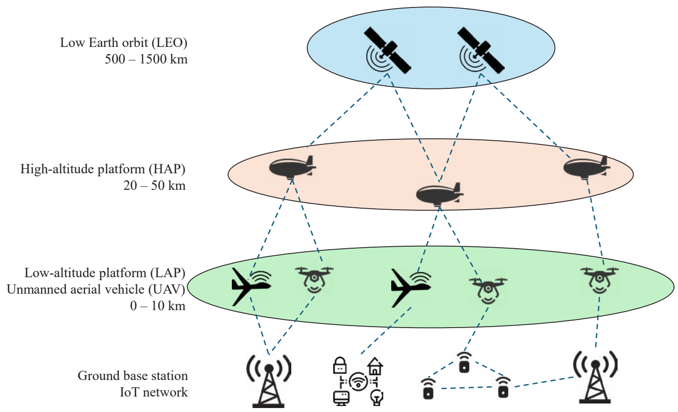

Fig. 1. Basic architecture of aerial access networks.

of minutes to several hours. HAPs, positioned in the stratosphere 20-50 kilometers above the ground, remain relatively stationary [5]. They form networks using optical connections. Their high altitude allows for wide coverage, reaching up to 100 kilometers in diameter at a 10-degree elevation. This means fewer HAPs are needed for extensive coverage, accelerating deployment. Compared to satellite systems, HAP communication systems offer lower costs, reduced latency, faster construction, and higher capacity.

A key advantage of AANs is their rapid deployment, making them ideal for emergencies and temporary events. Additionally, their flexibility allows for easy repositioning of aerial platforms to adapt to changing connectivity needs. AANs can expand network coverage to areas that are difficult or expensive to reach with traditional infrastructure [6]. In some cases, AANs offer a cost-effective alternative to ground-based infrastructure. However, AANs also introduce several new challenges, including:

- Dynamic Network Topology: UAVs constantly move, leading to rapid changes in network topology, which requires efficient and adaptive resource allocation algorithms.
- Heterogeneous Traffic Patterns: AANs serve diverse users with varying traffic demands, necessitating intelligent traffic management and load-balancing strategies.
- Interference Management: Co-channel interference among UAVs and terrestrial base stations can degrade network performance, demanding sophisticated interference mitigation techniques.
- Energy Efficiency: UAVs have limited battery life, necessitating energy-efficient operation and resource allocation to prolong network lifetime.
- Security and Privacy: AANs are vulnerable to various security threats, such as eavesdropping and jamming, while also handling sensitive user data.

To achieve optimal performance, advancements in communication system design must be paired with effective artificial intelligence solutions that integrate AANs into 6G systems.

III. GenAI for Aerial Access Networks

A. GenAI

GenAI is a subfield of artificial intelligence (AI) that focuses on developing systems capable of producing novel and creative content, including text, images, audio, and video [7]. Traditional AI models analyze data to make predictions or classifications. On the other hand, generative models learn patterns from existing data and produce new data instances with similar characteristics. GenAI comes in two forms: model-based and data-based. Both types learn from data, but data-based models use algorithms, while model-based models rely on predefined structures. Numerous GenAI models have been developed as follows.

- Generative Adversarial Networks (GANs) [12]: GANs comprise a generator network that synthesizes new data samples and a discriminator network tasked with discerning between authentic and generated data. The adversarial interaction between these networks drives the generator to produce increasingly realistic outputs.
- Variational Autoencoders (VAEs) [13]: A VAE employs a probabilistic framework to encode and decode data. The encoder maps inputs to a latent space distribution, while the decoder generates outputs from samples drawn from this distribution. Neural networks are trained to learn these probabilistic mappings, resulting in a powerful encoding-decoding system.
- Diffusion Models [14]: These utilize a two-step process. A forward diffusion process progressively adds Gaussian noise to an input, while a reverse diffusion process trains a model to reverse this process and recover the original data. This approach aims to maximize the likelihood of the training data.
- Transformer-based Models [15]: A transformer mainly includes tokenizers, embedding layers, and transformer layers. The major idea behind the transformers is called attention or self-attention which enables detection of the subtle relationships of sequential data even when the data elements are distant. A self-attention layer encodes each input entity with the global contextual information from the complete input sequence. Furthermore, multi-head attention uses multiple self-attention blocks to capture multiple relationships in the input sequence, allowing for parallel processing and scalability to highly complex models and large data sets. Models such as OpenAI's GPT-4 and DALL-E are examples of transformer-based GenAI.

B. Recent Studies on GenAI for AANs

GenAI offers significant advantages over conventional AI methods in the context of aerial access networks. Its ability to generate new content, learn from data, and adapt to changing conditions makes it a valuable tool for addressing the unique challenges of aerial networks. By leveraging the power of GenAI, we can develop more resilient, efficient, and secure aerial communication systems. In the following, we examine contemporary studies focusing on the application of GenAI to AANs.

A 6G framework proposed in [16] leverages actor-critic reinforcement learning and generative models to estimate line-of-sight probabilities and schedule traffic across terrestrial and non-terrestrial links. By transforming a partially observable environment into a fully observable one using GANs and VAEs, the agent learns optimal policies for channel selection and traffic scheduling, minimizing end-to-end losses and bandwidth usage. Simulation results demonstrate the effectiveness of this approach in achieving optimal transmission policies and reducing network overhead.

The study [17] proposed a Long Short-Term Memory (LSTM) and GAN-based method for predicting satellite network traffic. To address the challenges posed by the dynamic nature of satellite networks, the authors construct a simulated dataset reflecting population distribution density. To mitigate overfitting during training, the dataset is augmented using GAN. The LSTM-based model trained on this augmented dataset achieves a prediction accuracy of 95.43%, offering valuable insights for coordinating satellite network resource scheduling.

The paper [18] proposed a novel channel model for 5G-enabled maritime UAV communications utilizing millimeter wave (mmWave) technology. The model leverages an LSTM-based Distributed Conditional GAN to accurately estimate channel state information (CSI) for each beamforming direction. It is also employed to design a UAV network where each UAV learns mmWave CSI for all distributions. Comparative analysis with other state-of-the-art approaches demonstrates the superior performance of the proposed model in terms of accuracy, learning speed, and downlink data rates.

DroneDefGANt [19] is a GenAI-based approach designed to safeguard AAN from both external and internal threats. By leveraging the power of generative adversarial networks (GAN) and transformer models, DroneDefGANt effectively detects and prevents cyberattacks such as GPS spoofing, jamming, and actuator faults. The adaptive learning of the model ensures its resilience against evolving threats. Through rigorous evaluations using synthetic datasets, DroneDefGANt outperformed traditional AI models, demonstrating exceptional accuracy and robustness, especially in the face of noise-induced disturbances.

The work [20] proposed a new data augmentation algorithm for AI-enabled acquisition, tracking, and pointing systems in free-space optical communication. The algorithm combines wavelet transform with the fusing-and-filling GAN model to generate more diverse and detailed synthetic training data. Experimental results validate the superior performance of the proposed method over the baseline, as evidenced by significant improvements in image quality metrics.

The paper [21] introduced a federated learning-based GAN (FL-GAN) for air-to-ground channel estimation in mmWave wireless networks. This decentralized approach overcomes the limitations of centralized methods by learning from diverse data distributions across different geographical regions. The FL-GAN generates realistic channel patterns without requiring prior data analysis, ensuring adaptability to various environments. The FL-GAN's effectiveness in generating realistic synthetic data is confirmed by evaluation metrics such as Kullback-Leibler divergence and Wasserstein distance.

The DP-GAN scheme [22] addresses the limitations of existing drone pilot identification systems by employing a GAN-based approach. The scheme utilizes an LSTM-based generator to estimate the distribution of collected data and generate realistic flight data, thereby improving identification accuracy. A three-stage adversarial training strategy further optimizes the generator and discriminator, enhancing overall performance. Experimental results demonstrate the effectiveness of the DP-GAN scheme in achieving high accuracy rates under various conditions. Due to its low computational overhead, the DP-GAN scheme is well-suited for deployment on drone platforms for real-time pilot identification.

In [23], the authors introduced a novel convolutional autoencoder-aided sparse code multiple access system for satellite-terrestrial communications, utilizing a conditional Wasserstein generative adversarial network with gradient penalty (CWGAN-GP)-based channel modeling approach. The system leverages convolutional neural networks to construct the encoder and decoder, mitigating the curse of dimensionality. By using the received signal corresponding to the pilot symbol as conditional information, the CWGAN-GP effectively models the satellite-terrestrial fading channel. The proposed approach demonstrates superior performance over existing methods, as evidenced by lower bit error rates, block error rates, and computational complexity.

The study [24] examined rate-splitting multiple access networks enhanced by aerial intelligent surfaces with the aim of optimizing the trajectories of UAVs for user tracking. Two models, utilizing LSTM and Transformers, are developed to predict UAV positions. The Transformer-based model demonstrates superior robustness to variations in user locations, leading to more accurate predictions and consequently higher sum rates compared to the LSTM-based model.

In [25], the authors explored the potential of LLMs as a cornerstone for intelligent network control within 6G integrated terrestrial and non-terrestrial network environments. The proposed framework is structured to incorporate several critical components, each playing a pivotal role in ensuring optimal and intelligent control across the integrated network.

C. Challenges

While there is burgeoning interest in the application of GenAI to AANs, several significant challenges persist. The integration of GenAI into the AAN system necessitates real-time processing and decision-making capabilities to ensure optimal network performance. The dynamic and multifaceted nature of the AAN demands systems and algorithms that can process and react swiftly. Any latency in response could severely compromise the network's effectiveness, highlighting the urgency of designing efficient and responsive systems.

Furthermore, the introduction of GenAI into AAN introduces additional computational and communication complexities. Sophisticated GenAI technologies, such as GANs and VAEs, can increase computational overhead and processing time. It is essential to efficiently manage this integration overhead to ensure that the enhanced capabilities do not compromise system performance or network efficiency.

The distributed nature of AANs poses significant scalability challenges for GenAI integration. As the network expands and the volume of data processed increases, the demand for GenAI technologies will grow exponentially. The ability of GenAI models to scale effectively without compromising performance or network reliability is paramount for the successful deployment of GenAI-enabled AANs. This requires efficient distributed training and inference techniques, as well as robust mechanisms for handling large-scale data sets and complex network topologies.

IV. Future Outlook

A. Hybrid AI Architectures

The fusion of GenAI with other AI paradigms, e.g., reinforcement learning and deep learning, promises to elevate the effectiveness and resilience of AANs. For instance, the synergistic combination of GANs with deep reinforcement learning, as in [26], can result in highly skilled reinforcement learning agents exposed to a diverse range of network conditions. To safeguard data privacy while training GenAI models across multiple aerial platforms, the development of distributed learning frameworks, such as federated learning, is imperative [21]. Such frameworks can enable collaborative model training without compromising the confidentiality of sensitive data. Ensuring the transparency and interpretability of GenAI models is a paramount concern. Investigating techniques to make these models more explainable will facilitate greater trust and understanding of their decision-making processes.

B. Multi-modal Integration for Holistic Connectivity

The integration of diverse data modalities, including images, videos, audio, and radar scans, from satellites to ground sensors, offers a rich source of information for AANs. GenAI can play a pivotal role in seamlessly fusing this multimodal data, providing a more comprehensive understanding of the operating environment. By integrating multi-modal data, UAV networks can generate a holistic environmental model, enabling more informed and contextually aware decision-making. The protection of GenAI models against adversarial attacks is a critical challenge. Lightweight and effective solutions, potentially leveraging large language models for data recovery and reinforcement learning for enhanced security, are necessary to defend against the vulnerabilities exploited by these attacks.

C. Large Language Models

LLMs have emerged as powerful tools for optimizing existing systems by learning from application behavior. Their ability to understand, generate, and translate human-like text, honed through extensive training on large datasets, makes them invaluable across various domains, including robotics, healthcare, finance, education, customer service, and content creation. Recent technological breakthroughs have significantly enhanced aerial platform capabilities. Modern aeria platforms such as UAVs and HAPs are now equipped with powerful hardware that allows them to run LLMs directly on board, reducing dependence on cloud-based processing. This enables them to perform tasks such as real-time language translation, communication during international surveillance missions, and the analysis of complex sensor data using LLMs for dynamic decision-making in critical scenarios [8], [25], [27].

For example, predictive maintenance applications employ LLMs to anticipate network failures by analyzing historical performance patterns, thereby substantially reducing downtime and maintenance expenses. In the realm of personalization, LLMs leverage user data to customize services, enhancing user experiences through tailored content delivery and service offerings. Moreover, in AAN-assisted smart cities, LLM-driven IoT applications optimize traffic flow and energy distribution, contributing to more sustainable urban development. Finally, in AAN-based autonomous systems, LLMs facilitate real-time data processing, enabling autonomous IoT devices to make informed decisions, thereby improving safety and efficiency.

D. Standardization and Real-World Deployments

While standards bodies such as 3GPP and O-RAN Alliance have begun to embrace AI [1], the integration of GenAI in communication network standards remains largely unexplored. Standardization efforts should focus on ensuring interoperability and compatibility between different GenAI models and platforms. Future work should prioritize a gradual, systematic approach to integrating GenAI or LLMs into AAN systems. This will ensure compatibility, performance, and the ability to adapt to evolving technologies through regular updates, maintenance, and dedicated training. Moreover, conducting large-scale field trials is essential to validate the performance and benefits of GenAI-powered UAV networks in real-world scenarios.

By addressing these issues, we can significantly advance the reliability and effectiveness of mission-critical communications in AAN systems, paving the way for a more secure and efficient future.

V. Conclusion

This paper has explored the transformative potential of GenAI in revolutionizing AANs. By harnessing the capabilities of GenAI, AANs can achieve significant advancements in network management, optimization, and security. Our review of recent studies highlights the effectiveness of GenAI in various AAN applications, demonstrating its potential to address key challenges. While significant progress has been made, several challenges remain, including computational overhead, data privacy, and adversarial attacks. To fully unlock the potential of GenAI in AANs, future research should prioritize the development of more efficient algorithms, robust security measures, and standardized frameworks.

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