Generative AI for Advanced UAV Networking

Geng Sun, Wenwen Xie, Dusit Niyato, *Fellow, IEEE*, Hongyang Du, Jiawen Kang, Jing Wu,
Sumei Sun, *Fellow, IEEE*, Ping Zhang, *Fellow, IEEE*

***Abstract*—With the impressive achievements of chatGPT and Sora, generative artificial intelligence (GAI) has received increasing attention. Not limited to the field of content generation, GAI is also widely used to solve the problems in wireless communication scenarios due to its powerful learning and generalization capabilities. Therefore, we discuss key applications of GAI in improving unmanned aerial vehicle (UAV) communication and networking performance in this article. Specifically, we first review the key technologies of GAI and the important roles of UAV networking. Then, we show how GAI can improve the communication, networking, and security performances of UAV systems. Subsequently, we propose a novel framework of GAI for advanced UAV networking, and then present a case study of UAV-enabled spectrum map estimation and transmission rate optimization based on the proposed framework to verify the effectiveness of GAI-enabled UAV systems. Finally, we discuss some important open directions.**

***Index Terms*—Generative AI, UAV communications and networking, optimization, UAV spectrum estimation, diffusion model.**

I. Introduction

From rule-based algorithms to advanced learning models, the tasks that artificial intelligence (AI) can solve have become increasingly complex, which makes it demonstrate enormous potential for solving problems in industry, business and everyday life. Traditional AI methods, such as discriminative AI (DAI) or predictive AI (PAI), can learn special paradigms from large-scale datasets to handle classification and prediction tasks by utilizing deep neural networks. Although these AI methods provide the foundation for modern data-driven environments and demonstrate good performance in handling dynamic demands, they still face several problems, *e.g.*, it relies on widely annotated datasets.

Fortunately, the emergence of generative AI (GAI) has alleviated the limitations faced by DAI and PAI, marking a new stage in the AI development. Specifically, GAI can learn the probability distribution from training data instead of class boundaries, and then generate trustworthy new samples based on the learned distribution. Compared to traditional AI methods, the advantages of GAI can be summarized as follows:

- **Data Enhancement**: GAI has the capability to generate new data based on the learned distribution. This process can expand the training set, which helps to enhance model generalization and address dataset scarcity.
- **Latent Space Representation**: GAI can map the input data to the latent space during the training process, which contributes to learning the latent structure and features of the training samples. Note that this fine control is typically lacking in traditional AI methods.
- **Creativity**: Given the powerful generative ability of GAI and its outstanding performance in unsupervised learning, GAI has the advantages in exploratory data analysis and new field applications.

Benefiting from the abovementioned advantages, the importance of GAI in complex task processing has gradually emerged. In particular, the great success of ChatGPT[1] and Sora[2] has ignited GAI research and spawned a multitude of applications including human-computer interaction, image processing, and content understanding[3]. For example, the authors in [1] emphasize ChatGPT-based text knowledge bases for improving text comprehension and question answering in semantic communication. We can draw insights from this work, as the generative and exploratory capabilities of GAI offer potential for complex optimization problems, such as unmanned aerial vehicle (UAV) communication and networking optimization.

However, little research has been done on GAI for UAV communications and networking. Currently, DAI, convex optimization, and game theory are commonly adopted for solving UAV optimization problems. However, these traditional methods may have limitations in dealing with the UAV networking

This research is supported by National Natural Science Foundation of China (62272194, 62471200), the Science and Technology Development Plan Project of Jilin Province (20230201087GX), the National Research Foundation, Singapore, and Infocomm Media Development Authority under its Future Communications Research & Development Programme, Defence Science Organisation (DSO) National Laboratories under the AI Singapore Programme (FCP-NTU-RG-2022-010 and FCP-ASTAR-TG-2022-003), Singapore Ministry of Education (MOE) Tier 1 (RG87/22), and the NTU Centre for Computational Technologies in Finance (NTU-CCTF). (*Corresponding Author: Jing Wu.*)

Geng Sun is with the College of Computer Science and Technology, Jilin University, Changchun 130012, China, and with Key Laboratory of Symbolic Computation and Knowledge Engineering of Ministry of Education, Jilin University, Changchun 130012, China, and also with the College of Computing and Data Science, Nanyang Technological University, Singapore 639798 (e-mail: sungeng@jlu.edu.cn).

Wenwen Xie and and Jing Wu are with the College of Computer Science and Technology, Jilin University, Changchun 130012, China (e-mail: xieww22@mails.jlu.edu.cn, wujing@jlu.edu.cn)

Dusit Niyato is with the College of Computing and Data Science, Nanyang Technological University, Singapore 639798 (e-mail: dniyato@ntu.edu.sg).

Hongyang Du is with the Department of Electrical and Electronic Engineering, The University of Hong Kong, Hong Kong 999077, China (email: duhy@hku.hk).

Jiawen Kang is with the School of Automation, Guangdong University of Technology, Guangzhou, 510006, China (e-mail: kavinkang@gdut.edu.cn)

Sumei Sun is with the Institute for Infocomm Research, Agency for Science, Technology and Research, Singapore 639798 (e-mail: sunsm@i2r.a-star.edu.sg)

Ping Zhang is with the State Key Laboratory of Networking and Switching Technology, Beijing University of Posts and Telecommunications, Beijing 100876, China (e-mail: pzhang@bupt.edu.cn).

[1] https://openai.com/blog/chatgpt/
[2] https://openai.com/sora
[3] https://www.coursera.org/articles/generative-ai-applications

problems due to the mobility of UAVs and the highly dynamic environments. Moreover, learning methods such as DAI may fail to capture the latent structure and features of the data, which results in incomplete understanding of the problem and weak ability to handle the unknown situations.

GAI shows great potential for solving the issues above. Specifically, the powerful learning and generalization capabilities demonstrated by GAI can be used to optimize resource management problems in UAV networks for improving the communication performance. For example, considering the limited resources of UAVs, GAI can accurately infer the condition of the overall target area based on the data collected from part of the target area, thereby making reasonable resource allocation and trajectory planning. Although integrating GAI into UAV communications and networking offers significant advantages, there are still some issues that need to be further discussed:

- **Q1**: Why is GAI suitable for UAV communications and networking?
- **Q2**: What UAV communication and networking issues can GAI handle?
- **Q3**: How does GAI handle these issues?

Therefore, we provide a systematic tutorial to answer the above questions. *To the best of our knowledge, this is the first work to systematically demonstrate the adoption of GAI to solve UAV communication and networking optimization problems.* Our contributions are summarized as follows:

- We first introduce some specific technologies and applications of GAI. Subsequently, the roles and characteristics of the UAV are demonstrated. Finally, we illustrate the limitations of DAI and briefly present GAI for UAV communications and networking.
- We discuss the potential of GAI to address UAV-related issues from the perspectives of communication, network, and security.
- We propose a novel framework for UAV communications and networking leveraging GAI. Moreover, we construct a case study to demonstrate the effectiveness of GAI for enhancing UAV-enabled spectrum sensing and communication based on the proposed framework.

II. Overview of GAI and UAV Networking

In this section, we first introduce the key technologies and applications of GAI. Subsequently, the roles of UAV in networking are presented. Finally, we illustrate GAI on UAV in physical, network, and application layer.

A. GAI and Applications

GAI is based on massive general-purpose knowledge obtained from large-scale training datasets, and it can perform tasks that meet the needs of the users. Moreover, it mainly relies on the following key AI technologies:

- **Large Language Model (LLM)**: LLM is trained based on a large amount of text data to learn various language patterns and structures for the purpose of understanding and generating natural language. Based on the excellent comprehension and inference generation capabilities, LLM is widely used in the fields of text generation and human-computer interaction, *etc*.
- **Transformer**: Transformer is a sequence-to-sequence model with self-attention mechanism, which can simultaneously process information from various positions in the input sequence. Therefore, Transformer has achieved great success in natural language processing (NLP), such as machine translation and text summarization.
- **Generative Adversarial Network (GAN)**: GAN consists of a generator model and a discriminator model. Specifically, The former is responsible for generating similar data to the original data, while the latter is to determine the authenticity of the data. Currently, GAN has a wide range applications in the fields of videos and network security,*etc*.
- **Variational Autoencoder (VAE)**: VAE is a generative model consisting of an encoder and a decoder. Specifically, the training process of VAE relies on a specific loss function that measures the difference between the reconstructed data and the original data, while considering the distribution characteristics of the latent space. Thus, VAE has significant advantages in handling tasks such as signal processing and anomaly detection.
- **Generative Diffusion Model (GDM)**: GDM converts simple noise distributions into target data distributions through a series of reversible transformations. During the training process of the GDM, noise is gradually added to the original data, and then the inverse diffusion process is learned to construct the desired data samples from the noise. GDM is often employed in the fields of image processing, data enhancement and recovery, and problem optimization, *etc*.

Currently, GAI methods have spawned a lot of applications in various fields and achieved impressive results. Next, we will briefly introduce some GAI applications from the perspective of AI-Generated Content (AIGC) and AI-Generated Everything (AIGX).

- **AIGC**: AIGC refers to generating contents that meet the needs of users by GAI, mainly including the generation of media content such as text, image, video and audio. For example, LLM-based chatGPT can interact with the users and generate relevant text content according to the prompts of users, such as translations, summaries, and writing articles.
- **AIGX**: With the development of GAI, it has evolved to a new stage where GAI is employed to handle more complex problems in other domains and generate more complicated types of data, rather than being limited to media contents. Notably, GDM can be used in wireless network optimizations, such as maximizing the transmission rate, communication capacity, and energy efficiency.

The powerful problem understanding and processing capabilities that GAI have demonstrated in the abovementioned domains inspire us to apply it to solve the challenging UAV communication and networking optimization problems.

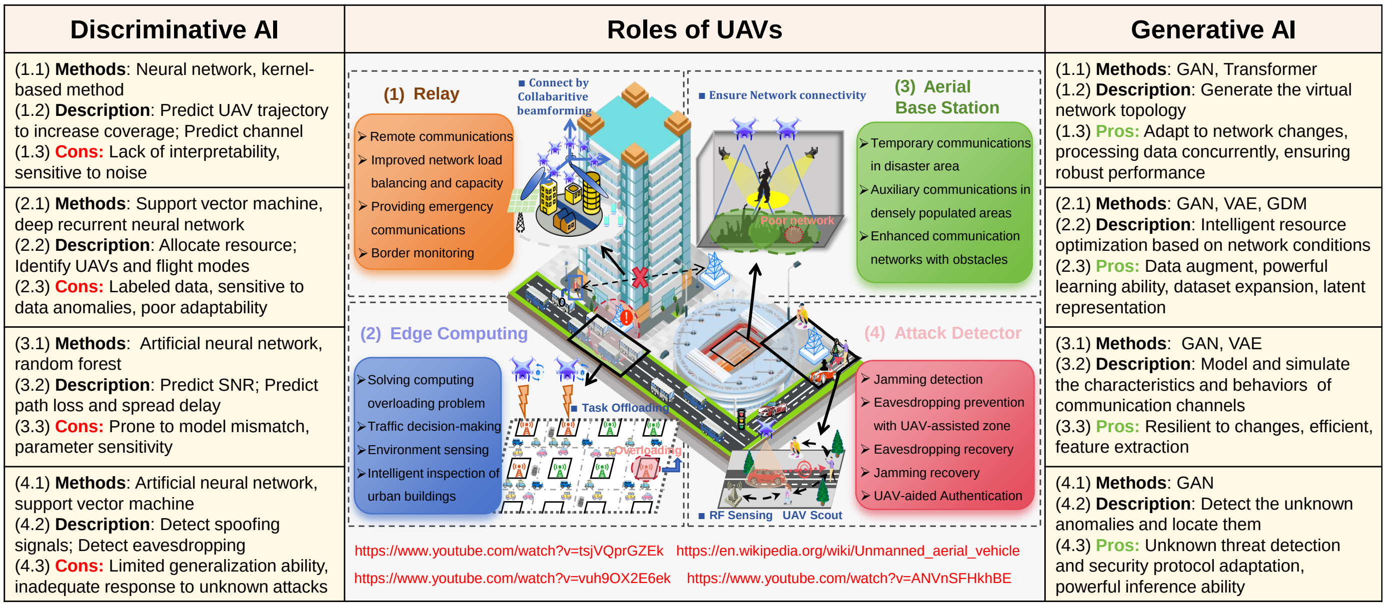

Fig. 1. The roles of UAVs in communications and networking and the comparison of DAI and GAI in solving UAV optimization problem. Due to its maneuverability and computing power, the UAV can act as the aerial base station, relay and edge computing device to solve the communications and networking problems in various scenarios. Moreover, DAI and GAI are widely used to solve optimization problems in the aforementioned scenarios, where GAI stands out due to its powerful generation and learning capabilities.

B. UAV Communications and Networking

UAV communication and networking systems have already achieved significant results in practical applications. Several main roles of UAV systems are shown in Fig. 1, which can be detailed as follows.

- **Relay**: UAVs can be utilized as mobile relay stations to connect the communication links between ground base stations and remote devices [2]. For example, in some special areas such as mountainous regions, where traditional base stations are difficult and costly to cover, UAVs can be assigned as relays to expand coverage and achieve long-distance transmission of signals.
- **Aerial Base Station**: UAVs can be used as aerial base stations to provide stable and efficient communication services to ground users [3]. For example, UAVs can be used as temporary communication base stations in densely populated areas to enhance communication coverage and capacity to meet the peak communication needs.
- **Edge Computing**: UAVs can act as edge computing devices to collect data from users for real-time analysis and processing [4]. For example, in intelligent traffic management, UAVs can analyze the current traffic conditions based on the obtained traffic flow statistics to make timely traffic control adjustments, which can alleviate traffic pressure.
- **Attack Detector**: Given their versatility, UAVs can be utilized to assist in the prevention, detection, and recovery of attacks on 5G and 6G wireless networks [5].

The widespread applications of UAV communication and networking systems are inevitable due to their advantages over traditional terrestrial systems, which are summarized as follows.

- **Flexibility**: Due to their high mobility and flexible deployment capability, UAVs can move quickly to specific areas to meet the communication requirements.
- **Adaptability**: UAV can build temporary networks for some unexpected scenarios, supporting the temporary addition or withdrawal of UAV nodes while maintaining high availability.
- **High Cost-effectiveness**: Compared to terrestrial fixed systems, UAVs can carry multiple devices for providing flexible and diverse services. Moreover, the cost of UAV systems is typically lower.

Due to the aforementioned advantages and applications, UAV systems have been considered as an important part in space-air-ground-sea integrated networks for 6G. Therefore, it is crucial to efficiently solve the problems faced by UAV communications and networking more efficiently.

C. GAI for UAV Communications and Networking

Note that some DAI methods are used to solve the optimization problems in UAV systems. However, it cannot be ignored that DAI methods still face the following limitations [6].

- **Data Dependency**: DAI methods depend on annotated datasets, and they require a large volume of labeled data to learn data relationships. However, acquiring such data in UAV communications and networking is difficult, especially in physical layer.
- **Weak Adaptability**: DAI focuses more on patterns and features of known data, which leads to challenges when dealing with the unknown situations. In particular, the environments faced by the network layer of UAVs are often highly dynamic, hence DAI may struggle to provide flexible solutions.

- **Insufficient Modeling Capabilities**: DAI emphasizes data features with limited insight into data generation processes and latent representation. Thus, DAI methods are more suitable for modeling clear and simple problems, rather than highly dynamic and complex systems like UAVs.

The limitations faced by DAI methods in solving the UAV communication and networking problems lead to an increased interest in GAI. This is due to the following characteristics of GAI that make it more suitable for UAV systems compared to DAI:

- **Data Augmentation**: GAI can learn the distribution of training samples to generate highly similar data to alleviate the data scarcity. Moreover, GAI generates diverse and high-quality training data, which helps to discover optimal decisions for UAVs as well as improve the robustness of UAV systems.
- **Integration of Multiple Data Sources**: GAI can integrate information from various sensors and data sources, such as GPS, cameras, and radar, providing comprehensive situational awareness and decision support for UAVs.
- **Superior Reasoning Ability and Knowledge Transfer**: GAI can analyze and predict based on historical and real-time data, which is crucial for the highly dynamic systems like UAVs. Moreover, GAI can transfer the learned knowledge, which significantly enhances the adaptability and stability of UAV systems in diverse settings.

In the following, we show services that GAI can provide to UAVs from three perspectives, namely, the physical layer, network layer, and application layer. Moreover, we further analyze the differences between UAV systems and other wireless systems in these services.

*1) **Physical Layer**:* Compared to terrestrial communication systems, the highly dynamic and flexible nature of UAV networks makes the channel characteristics more complex. Therefore, the channel estimation requires to consider the changes of flight state in real-time for the purpose of maintaining a stable and efficient communication connection. In such cases, GAI with VAE model [7] can improve the performance of UAV communications by generating more accurate channel parameters according to the predicted link state.

*2) **Network Layer**:* In traditional terrestrial systems, the positions of nodes are typically fixed and the communication paths are relatively stable. In contrast, due to the mobility of UAVs, the network topology of UAV systems is more flexible and dynamic. In this case, GAI can generate adaptive network topology management schemes in real-time to adapt to different communication scenarios according to task requirements. For example, WaveGAN method [8] is proposed to optimize the network topology in the integration of dynamic flying ad-hoc networks.

*3) **Application Layer**:* The diverse mission requirements and real-time data processing capabilities of the UAV at the application layer make it significantly different from other wireless systems. Moreover, due to the resource-constrained nature of UAVs, higher demands are placed on the process of resource allocation, and trade-off between multi-objectives, *etc*. In this instance, GAI can generate intelligent resource allocation and task scheduling solutions according to the real-time demand of the current missions and environment changes, which can ensure various performances of the UAV systems. Specifically, a typical example is a GAN-based method [9] to minimize the energy consumption of UAVs and task latency of ground users.

III. GAI-enhanced Technologies in UAV Communications and Networking

In this section, we show how GAI addresses the optimization problems from UAV communication, network and security perspectives, which are summarized in Table I.

A. From Communication Perspective

*1) **Interactive strategy optimization**:* Proper scenario simulations and correct problem formulations are cornerstones for optimizing the performance of the UAV communication and networking systems. In [10], the authors propose a problem formulation framework based on LLM and retrieval augmented generation (RAG) for a wireless communication scenario. Specifically, the users provide some detailed information that are related to the scenario (*e.g.*, structure and optimization objectives) for the purpose of requiring the problem formulation. Then, based on the prompts of users, the GAI agent adopts RAG technology to generate corresponding problem formulation. An experiment validates the performance of LLM, where a GAI agent derives an optimization problem for a Simultaneous Wireless Information and Power Transfer (SWIPT) network based on the detailed scenario description. The results show that when using the LLM-based formulation, the performance is similar to that of the original paper and outperforms a manual design that ignores key constraints. This is due to the retrieval and inference capabilities of LLM in LangChain, which facilitates accurate problem generation with fewer interactions.

*2) **Adaptive Modulation and Channel Sensing**:* Given the constantly changing environments that UAVs operate in, conventional terrestrial energy and cyclic detection methods are less effective. In this case, we can employ GAI to analyze the collected environmental data in real-time to build channel model and adaptive modulation. For example, VAE can be used for channel sensing and modeling between the UAV and base station [7]. Specifically, a neural network is first utilized to predict the state of the communication link, which is subsequently input into the VAE to generate channel-related parameters such as path loss, delay, angle of arrival and angle of departure. Experimental results demonstrate that the proposed GAI-based model performed similarly or better than the refined 3rd Generation Partnership Project (3GPP) model in every environment. Moreover, it finds that the GAI model can capture complex relationships among paths, which are unaccounted for in standard parametric models. This performance improvement is due to the fact that the generative model is able to learn complex probabilistic relationships well with sufficient data.

TABLE I
THE USE OF GAI IN UAV COMMUNICATIONS AND NETWORKING.

Models / Issues	Generative AI Model					Analysis
	LLM	**Transformer**	**GAN**	**VAE**	**GDM**	
Iteractive Strategy Optimization	Learn historical relevant data [10]	—	—	—	—	Potential benefits: (1) More comprehensive problem understanding ability (2) More powerful channel sensing capability (3) More intelligent resource allocation and more rational network deployment
Adaptive Modulation and Channel Sensing	—	Predict future channels in parallel	Train a stand-alone channel model	Generate parameters related to channel [7]	—	
Communication Resource Allocation and Optimization	—	—	Provide an approximation of the distributions of UAVs [9]	Assign tasks to edge computing servers	Resource allocation strategy generation	
Route Design	—	Plan UAV cluster routing	Learn the routing policy [11]	—	Generate the routing strategies based on environment changes	Potential benefits: (1) Better routing policies for dynamic UAV environment (2) More rational UAV network topology for better performance (3) Improve the accuracy of network configuration
Network Topology Design	—	Plan long-term trajectory	Generate optimized network topology from supervised dataset [8]	—	—	
Network Configuration Optimization	Analyze network traffic	—	—	—	Generate customized network solutions for specific needs [12]	
Physical Layer Security	—	Predict the ideal serving beam for UAVs	Approximate mmWave channel distributions	Provide robust data transmission	Optimize beamforming and signal DoA estimation [13]	Potential benefits: (1) Optimize UAV beamforming (2) Improve the accuracy of network configuration (3) Enhance privacy protection capability in a novel way
Anomaly Detection	—	—	Detect the unknown anomalies and locate them [14]	Detect UAV faults and anomalies	Detect network intrusion	
Privacy Preservation	—	—	Generate training samples [15]	—	—	

*3) **Communication Resource Allocation and Optimization:*** GAI can simulate the environments to adjust resource allocation for efficiency and quality of task execution. For example, in [9], the authors propose a GAN-powered deep reinforcement learning (DRL) strategy for task offloading. Specifically, a GAN-based training mechanism for offline training via generated environment states is employed to address high online training cost and low sample efficiency of DRL algorithm. Experimental results show that the Jensen–Shannon (JS) divergence between GAN-generated task resource distributions and actual distributions is controlled at the 10^{-4} order of magnitude, indicating the authenticity of GAN samples. Moreover, the GAN-based DRL algorithm achieves near real-world delay performance while significantly reducing interaction costs. This improvement is due to the powerful distribution fitting of GAN, allowing offline training with limited real-world samples.

B. From Network Perspective

*1) **Route Design:*** The routing design of UAV networks is required to consider the factors of UAV mobility and environment dynamism, which suggests that more flexible routing algorithms and mechanisms should be adopted. In this case, a GAN-based method [11] called AR-GAIL is proposed to decide the route strategy of UAV networks. Specifically, GAN includes a discriminator to differentiate expert strategies from generated strategies and a generator to create expert-like routing strategies, enabling direct policy learning by mimicking expert behavior. Under different traffic loads, compared to the state-of-the-art DVN protocol, AR-GAIL improves average end-to-end delay, maximum end-to-end delay, and packet delivery rate by 27%, 33%, and 12%, respectively. The gains are attributed to the powerful learning ability of GAN, which allows AR-GAIL to internalize expert routing strategies and make near-optimal routing decisions even under unseen network conditions.

*2) **Network Topology Design:*** Intelligent network topology design is crucial for highly dynamic systems such as UAVs, which contributes to improving the network performance. In [8], the authors propose a GAN-based topology optimization method to enhance network throughput in dynamic UAV ad-hoc networks. Specifically, GAN learns from a supervised dataset of random three-dimensional (3D) UAV positions and corresponding optimal topologies, then generates optimized topologies for given positions, refined by a low-complexity beam search algorithm. Simulation results show that with 8 and 10 UAVs, the gaps from optimal topologies are 0% and 0.2%. Moreover, GAN-based method achieves an average throughput gap of 6.25% from the optimal solution, outperforming the greedy algorithm and 2-Opt heuristics, which have a gap of more than 30%. The improved performance is due to the adaptability and robustness of the GAN, which generates near-optimal or optimal solutions in real time for different network sizes.

*3) **Network Configuration Optimization:*** The task requirements of UAV systems have become more varied and complex, which means that UAV networks demand more intelligent and customized designs. In [12], the authors propose AI-Generated Network (AIGN) for customized network solutions. First, the LLM model compiles network design intent and generates explanations with constraints and requirements. Subsequently, the diffusion model is trained to create a network design

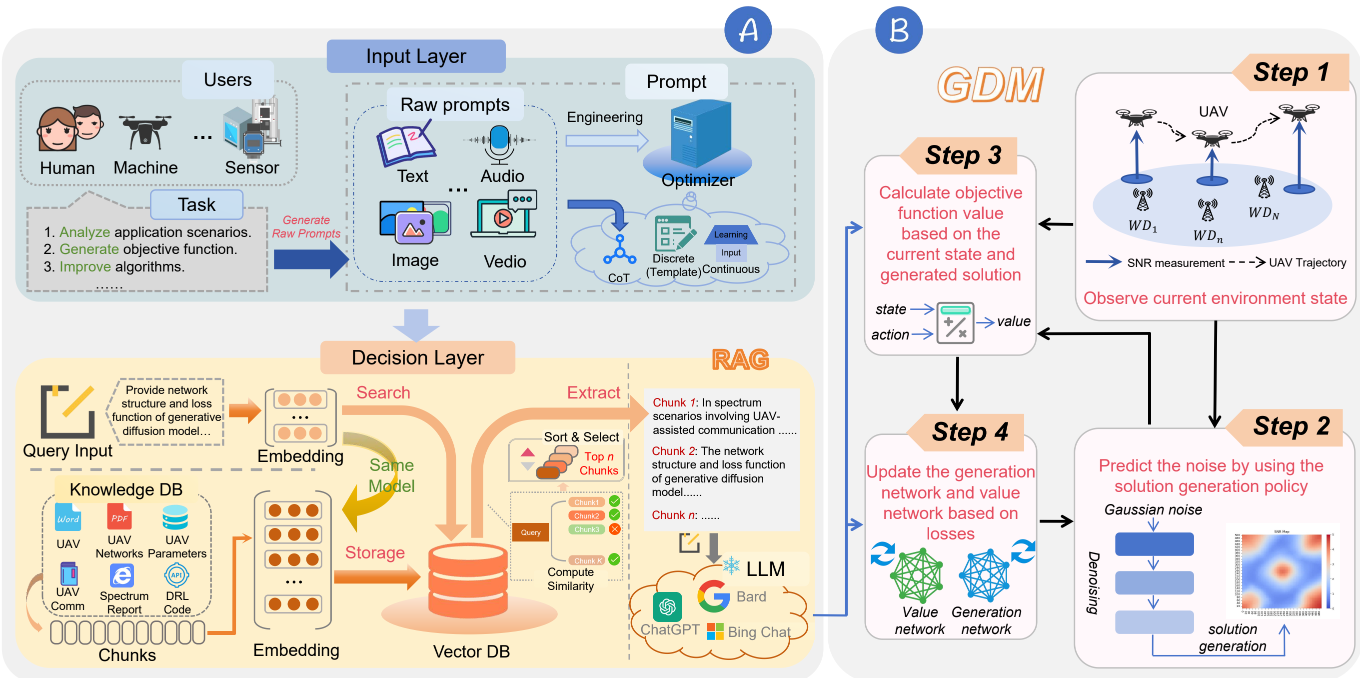

Fig. 2. The framework of the proposed SEMG. In part A, the prompt optimizer generates professional prompts based on the task of users (in our case study for constructing the objective function, the network structure and loss function of the diffusion model), and subsequently the RAG is employed to output the results. In part B, the diffusion model is used to generate the solution to the optimization problem. Specifically, in Step 1, the current state is obtained. In Step 2, the diffusion model generates the solution based on the state, *i.e.*, the SNR estimation. In Step 3, the objective function value is computed based on the observed state and the generated solution. In Step 4, the loss of the diffusion model network is calculated based on the objective function value and the network is updated.

meeting these conditions. Results show that the AIGN generates optimal allocations based only on channel gain and noise parameters in a power allocation case, and converges faster than SAC, despite similar performance. Note that the improvement relies on the conditional generation ability of diffusion model, overcoming dataset bias and adapting to the environment.

C. From Security Perspective

*1) **Physical Layer Security**:* Beamforming or collaborative beamforming is widely used in UAV physical layer security. In this case, GAI can optimize beamforming by learning the relationship between UAV antenna configurations and beamforming parameters. The authors in [13] propose a diffusion model-based signal spectrum generator (SSG) to estimate the direction of arrival (DoA) of signals in near-field conditions. SSG adds noise to expert solutions (clear signal spectra) and then denoises them progressively, refining the hyperparameters of the denoising network. Trained SSG generates clear spectra from ambiguous spectra, supporting DoA estimation in near-field systems. Experimental results show that the test reward of SSG exceeds DRL algorithms by 87.5%. Moreover, SSG reduces median localization error from 1.25 wavelength to 0.21 wavelength. The performance of SSG benefits from the inference and learning capabilities of diffusion model. Inspired by this work, GDM models can optimize UAV beamforming for better communication.

*2) **Anomaly Detection**:* UAVs are often subject to malicious node attacks due to deployment in open environments, making network intrusion detection essential for mission safety. In [14], a collaborative intrusion detection algorithm based on conditional GAN (CGAN) is proposed, in which long short-term memory (LSTM) is introduced into CGAN training to improve the feature extraction ability of the network. Specifically, the data generated by CGAN is used as the enhanced data for intrusion detection and classification. Experimental results show that the CGAN-based data augmentation improves classification accuracy by 25%, 67%, and 24% on the Bot, Infiltration, and Web_Attack datasets, respectively. Compared to support vector machine (SVM), random forest, and recurrent neural network (RNN), CGAN methods boost accuracy by 1.22% to 4.04%. This performance gain is due to the strong generative capabilities of GAN, which effectively address data imbalance and enhance model training accuracy.

*3) **Privacy Preservation**:* GAI can be used to protect sensitive data transmitted or shared within UAV networks from unauthorized access or surveillance. For example, a distributed GAN framework [15] is proposed to model millimeter wave (mmWave) channels by efficient, privacy-preserving data sharing within UAV networks.Specifically, the GAN is trained to generate channel samples based on the underlying distribution of its dataset, while maintaining data confidentiality by sharing generated data rather than real data samples with others. The results show that the proposed GAN-based method achieves over 10% higher downlink communication rates than baseline schemes, due to its distributed learning capabilities and privacy-preserving collaboration.

Lesson Learned: GAI effectively addresses data scarcity,

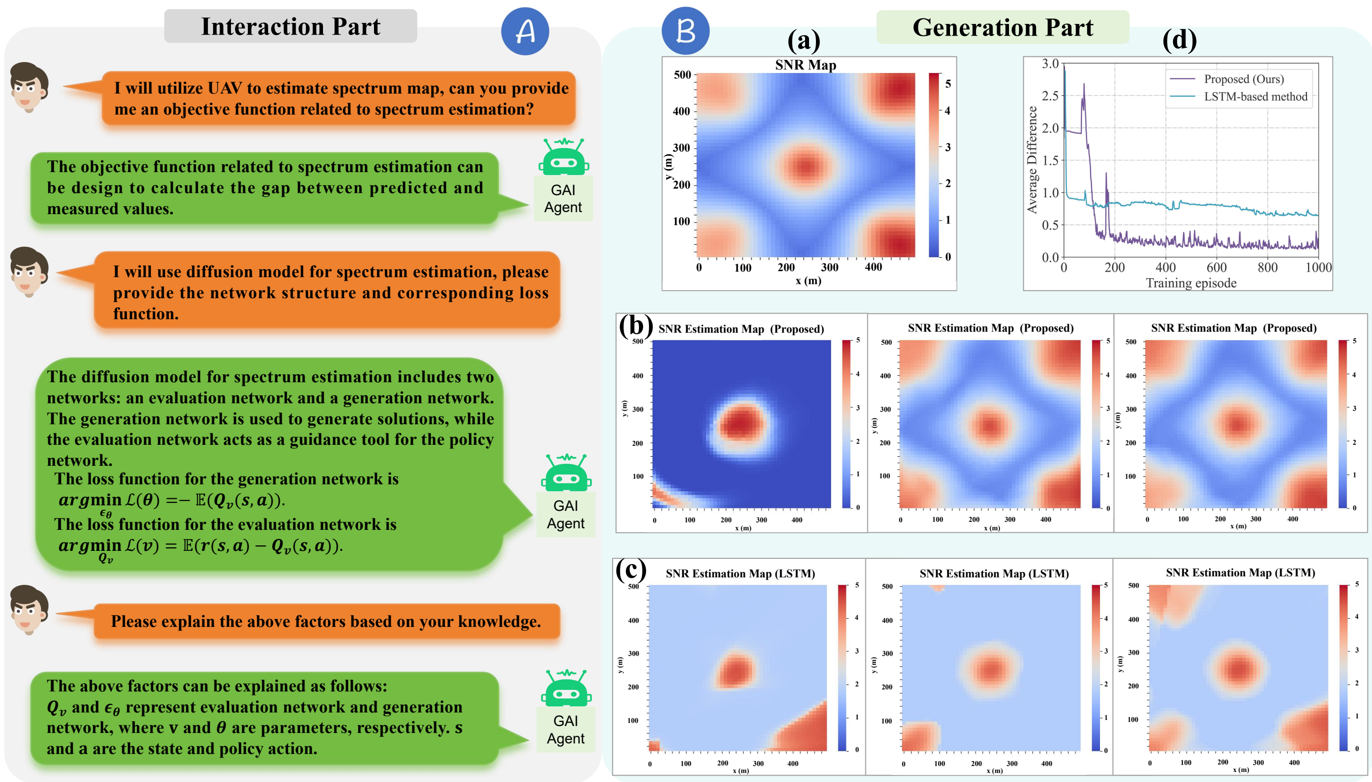

Fig. 3. The experiment result of spectrum estimation. Part A shows the interaction between the user and GAI agent for the purpose of constructing the objective function, the network structure and loss function of diffusion model. Part B demonstrates the generation performance of diffusion model. (a) the true SNR map. (b) the process of generating SNR estimation map by our proposed SEMG. (c) the process of generating SNR estimation map by LSTM. (d) the difference between the measurements and estimations.

significantly improving data quality and diversity. Moreover, the high-quality environment simulations generated by GAI can train the UAV systems to perform better in real environments, reducing errors and risks in real-world operations. Furthermore, the learning and reasoning abilities of GAI can boost the adaptability and decision-making accuracy of UAV systems. In addition, when integrated with other algorithms, GAI can further refine their decision-making for better UAV performance.

IV. Case Study: GAI for UAV Spectrum Map Estimation

In this section, we propose a novel framework for GAI on UAV spectrum estimation and present two case studies demonstrating its effectiveness. Specifically, the first case uses GAI to construct a spectrum estimation map from UAV measurements, while the second one optimizes UAV trajectory with GAI to improve transmission performance based on spectrum map.

A. Motivation

Spectrum cartography involves techniques for constructing radio maps to understand the radio frequency (RF) landscape, aiding complex tasks. Traditionally, technicians in a vehicle with measurement equipment would drive around the site to collect measurement. With advances in mobile robotics, it is possible to use UAVs with on-board sensors to collect the required measurement data, which is clearly more efficient in terms of time and labor costs.

Utilizing UAV data for spectrum estimation requires deep wireless network knowledge and complex professional methods. In this case, Compared to DAI, which lacks adaptability and generalization, GAI offers a more feasible solution, with diffusion models inferring the spectrum of target area from UAV data, enabling complex tasks. Note that the network structure and loss design in diffusion models are crucial for optimization. However, manual design is challenging, especially for newcomers. In this case, LLM interprets the scenario information defined by the designer and automatically construct the appropriate network structure and loss design, significantly reducing the risk of human error. Moreover, RAG technology is adopted to significantly improve the accuracy, reliability, relevance, and timeliness of LLM responses.

B. Proposed Design

As shown in Fig. 2, we propose a GAI-based UAV spectrum estimation map generator (SEMG), which contains the following components:

1) Interaction Part: In the input layer, users (*e.g.*, UAV operators) provide GAI with raw prompts based on task requirements, including text, images, audio and video, *etc*. Then, prompt engineering is adopted to optimize the prompts. In the decision layer, users can prepare some fresh or proprietary data which is relevant to their needs. Note that the prepared data above will be vectorized, indexed and stored in the vector database. Subsequently, the framework retrieves the vector database based on the query of the user and selects the N data entries with the highest relevance. After that, the selected data that is regarded as the background context is integrated with the query to form the prompts, which can better guide the LLM to generate appropriate strategies that meet the requirement of users.

2) Generation Part: First, the current state of the environment is observed. Subsequently, the diffusion model predicts noise and generates solution based on the observed state. Finally, the objective value is calculated and the networks of diffusion model are updated according to the objective function and loss function designed by LLM in the interaction part, respectively.

Next, We design two case studies to demonstrate the effectiveness of the proposed SEMG framework.

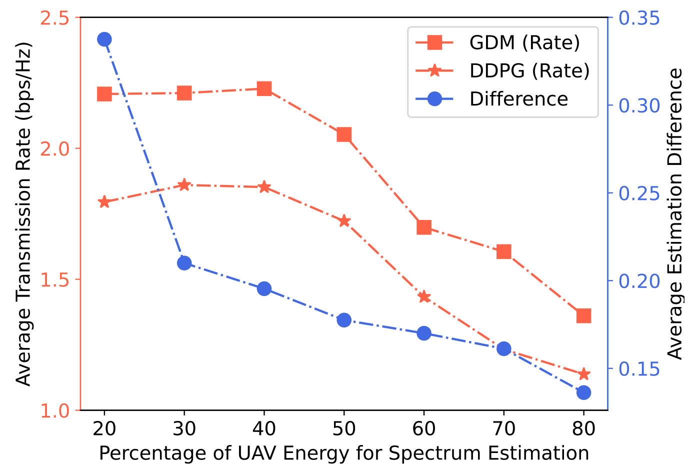

Fig. 4. The impact of percentage of estimation energy on spectrum estimation difference and transmission rate.

C. Case Study Setup

To clearly present the subsequent case study, we first introduce some key parameters involved in the simulation, as well as the experimental tools and environment.

1) Key Parameters: We set the size of chunks in the RAG to 2000. Moreover, the GAI agent retrieves 3 chunks to perform inference in each round [10]. Furthermore, we adopt a generative diffusion model consisting of a policy network and a value network, and both the networks consist of two hidden layers, in which each layer has 256 neurons. In addition, the minibatch size is 128, and the learning rates of both the policy and critic networks are 0.0003.

2) Environment and Tools: The server used for the experiment is equipped with an Intel i9 13900K CPU and an NVIDIA RTX 4090 GPU, and the RAM is a 32 GB DDR4. Moreover, the proposed SEMG framework is implemented by Python. Specifically, the pluggable LLM module is implemented by OpenAI API for calling the GPT-4 model, and the network-oriented knowledge base and context memory based on LangChain. Furthermore, the diffusion model is implemented by Pytorch.

D. Case 1: UAV-enabled Spectrum Estimation

1) Scenario Description: The UAV is dispatched to measure signal-to-noise ratio (SNR) data in a portion of the target area. Then, the diffusion model is adopted to optimize the measurement trajectory of the UAV to more accurately predict the spectrum map of the entire target area based on limited measurement information.

2) Performance Analysis: The interaction between the user and GAI agent is presented in Part A of Fig. 3. As can be seen, the GAI agent can automatically design a network structure and loss function that perfectly aligns with the ground truth during the interaction with the user. Based on the designed network structure and loss function, we can adopt diffusion model to generate spectrum estimation. Fig. 3(a) presents the true SNR map. Moreover, Fig. 3(b) and Fig. 3(c) shows the process of generating SNR estimation map by our proposed SEMG and LSTM, respectively. Compared to the spectrum map generated by LSTM, the diffusion model can more accurately infer the SNR of the whole target area. Furthermore, we define a metric called difference, which refers to the absolute value of the SNR gap between the estimated spectrum and the true spectrum. Fig. 3(d) shows the estimation difference of our proposed SEMG and LSTM, where our proposed SEMG outperforms LSTM. This is because the diffusion model can accurately capture the distribution of spectrum data. Therefore, the abovementioned results demonstrate the effectiveness of SEMG in UAV-enabled spectrum estimation.

E. Case 2: UAV-enabled Joint Spectrum Estimation and Rate Optimization

1) Scenario Description: In this scenario, the UAV acts as both spectrum estimator and data transmitter, and we aim to use diffusion model to generate the UAV exploitation trajectory for jointly achieving accuracy spectrum map and high transmission rate. Considering the energy constrained nature of UAV, the impact of energy consumption on spectrum estimation and transmission performance is necessary to explore.

2) Performance Analysis: Fig. 4 shows the impact of percentage of estimation energy consumption on spectrum estimation accuracy and transmission performance. As the energy allocated to spectrum estimation by UAV increases, the difference between the spectrum estimation map and true map gradually decreases. This is because more energy of UAV is allocated to spectrum detection will lead to more accurate spectrum estimation. However, UAVs are energy-constrained aerial platforms, and allocating more energy for spectrum estimation means less energy are available for data transmission. Therefore, the curve of transmission rate shows a decrease tend when the energy allocated to spectrum estimation increases. However, when the energy allocated to spectrum estimation is too low, the poor quality of spectrum estimation map affects the optimization data transmission rate. Note that our proposed GDM-based method outperforms deep deterministic policy gradient (DDPG), which means that it is especially suitable for the resource-limited UAV systems. This is because diffusion model can better model the complex mapping between states and actions. Moreover, diffusion model can generate diverse and high-quality samples, which helps the policy network to explore a wider range of actions. This enhanced exploration can lead to the discovery of better policies that might be missed by traditional DDPG methods.

V. Future Directions

In this section, we will introduce three future directions for GAI on UAV communications and networks.

A. Energy-Efficient GAI on UAVs

The inference of GAI involves complex computational processes, making it resource-intensive, particularly for the energy-constrained platforms such as UAVs. Therefore, incorporating the operating costs of GAI into UAV systems is a crucial direction to ensure the efficient utilization of resources for achieving optimal performance. One feasible approach involves offloading more intensive GAI computational tasks to edge servers, which allows UAVs to save on-board energy while still benefiting from the advanced GAI capabilities.

B. Secure GAI on UAV

The UAV wireless communications pose various attack threats due to the open channel. Although beamforming can resist eavesdropping attacks, it is powerless against data tampering by attackers. Note that blockchain-based data platforms are worth investigating in order to protect the data of GAI. This is because the decentralized and immutable ledger of blockchain ensures that once data is recorded, it cannot be altered without detection, making it an ideal solution for preventing data tampering. Therefore, by recording GAI data and communication logs on blockchain, UAVs can ensure that their data remains untampered and verifiable.

C. Multimodal Processing on UAV

The recent success of Sora has sparked a surge in video generation technologies. It is worth noting that UAVs are extensively utilized in high-altitude video capture applications. Consequently, leveraging GAI for real-time processing of UAV videos emerges as a compelling research avenue. Specifically, GAI models such as diffusion and GAN can be trained on a large amount of aerial camera datasets to learn how to seamlessly enhance resolution and apply stylized effects, and then integrated into UAVs to significantly improve the quality of real-time video streams.

VI. Conclusion

In this article, we systematically introduce how GAI optimizes the UAV communications and networking. Specifically, we first introduce the fundamentals of GAI and the multiple roles of UAVs. Then, we discuss GAI on UAV from three perspectives of communication, network, and security. Subsequently, we propose a novel framework of GAI for UAV communications and networking, and then conduct a case study on UAV-enabled spectrum map estimation and transmission rate optimization to validate the effectiveness of the proposed GAI framework. Finally, three key future directions are shown that can further improve GAI on UAV systems. We hope that this article can inspire researchers to propose more GAI methods in wireless network areas such as UAV networks.

References

[1] F. Jiang, Y. Peng, L. Dong, K. Wang, K. Yang, C. Pan, and X. You, "Large AI model-based semantic communications," *IEEE Wirel. Commun.*, vol. 31, no. 3, pp. 68–75, 2024.

[2] G. Sun, J. Li, A. Wang, Q. Wu, Z. Sun, and Y. Liu, "Secure and energy-efficient UAV relay communications exploiting collaborative beamforming," *IEEE Trans. Commun.*, vol. 70, no. 8, pp. 5401–5416, 2022.

[3] Q. Zhang, W. Saad, M. Bennis, X. Lu, M. Debbah, and W. Zuo, "Predictive deployment of UAV base stations in wireless networks: Machine learning meets contract theory," *IEEE Trans. Wirel. Commun.*, vol. 20, no. 1, pp. 637–652, 2021.

[4] G. Sun, L. He, Z. Sun, Q. Wu, S. Liang, J. Li, D. Niyato, and V. C. M. Leung, "Joint task offloading and resource allocation in aerial-terrestrial uav networks with edge and fog computing for post-disaster rescue," *IEEE Trans. Mob. Compu.*, pp. 1–18, 2024.

[5] A. S. Abdalla, K. Powell, V. Marojevic, and G. Geraci, "UAV-assisted attack prevention, detection, and recovery of 5G networks," *IEEE Wirel. Commun.*, vol. 27, no. 4, pp. 40–47, 2020.

[6] Z. Tu, "Learning generative models via discriminative approaches," in *IEEE CVPR*, 2007.

[7] W. Xia, S. Rangan, M. Mezzavilla, A. Lozano, G. Geraci, V. Semkin, and G. Loianno, "Generative neural network channel modeling for millimeter-wave UAV communication," *IEEE Trans. Wirel. Commun.*, vol. 21, no. 11, pp. 9417–9431, 2022.

[8] E. Odat, H. Ghazzai, and A. Alsharoa, "A WaveGAN approach for mmWave-based FANET topology optimization," *Sensors*, vol. 24, no. 1, p. 6, 2024.

[9] Y. Li, L. Feng, Y. Yang, and W. Li, "GAN-powered heterogeneous multi-agent reinforcement learning for UAV-assisted task offloading," *Ad Hoc Networks*, vol. 153, p. 103341, 2024.

[10] R. Zhang, H. Du, Y. Liu, D. Niyato, J. Kang, S. Sun, X. Shen, and H. V. Poor, "Interactive AI with retrieval-augmented generation for next generation networking," *arXiv preprint arXiv:2401.11391*, 2024.

[11] J. Liu, Q. Wang, and Y. Xu, "AR-GAIL: Adaptive routing protocol for FANETs using generative adversarial imitation learning," *Computer Networks*, vol. 218, p. 109382, 2022.

[12] Y. Huang, M. Xu, X. Zhang, D. Niyato, Z. Xiong, S. Wang, and T. Huang, "AI-generated network design: A diffusion model-based learning approach," *IEEE Network*, 2023.

[13] J. Wang, H. Du, D. Niyato, J. Kang, S. Cui, X. Shen, and P. Zhang, "Generative AI for integrated sensing and communication: Insights from the physical layer perspective," *arXiv preprint arXiv:2310.01036*, 2023.

[14] X. He, Q. Chen, L. Tang, W. Wang, and T. Liu, "CGAN-based collaborative intrusion detection for UAV networks: A blockchain-empowered distributed federated learning approach," *IEEE Internet Things J.*, vol. 10, no. 1, pp. 120–132, 2022.

[15] Q. Zhang, A. Ferdowsi, and W. Saad, "Distributed generative adversarial networks for mmwave channel modeling in wireless UAV networks," in *IEEE ICC*, 2021, pp. 1–6.

Biographies

Geng Sun (sungeng@jlu.edu.cn) received a B.S. degree in Communication Engineering from Dalian Polytechnic University, China, and the Ph.D. degree in Computer Science from Jilin University, China, in 2011 and 2018, respectively. He was a visiting researcher in the School of Electrical and Computer Engineering at Georgia Institute of Technology, USA. He is currently a Professor in the College of Computer Science and Technology at Jilin University, and his research interests include UAV Networks, collaborative beamforming, generative AI and optimizations.

WENWEN XIE (xieww22@mails.jlu.edu.cn) received the B.S. degree in Computer Science and Technology from Hefei University of Technology, Hefei, China, in 2022. She is currently working toward the MS degree in Computer Science and Technology at Jilin University, Changchun, China. Her research interests include UAV communications, IRS beamforming and deep reinforcement learning.

DUSIT NIYATO (dniyato@ntu.edu.sg) is currently a professor in the School of Computer Science and Engineering, Nanyang Technological University, Singapore. He received the B.Eng. degree from King Mongkut's Institute of Technology Ladkrabang (KMITL), Thailand, in 1999, and the Ph.D. in electrical and computer engineering from the University of Manitoba, Canada, in 2008. His research interests are in the areas of Internet of Things (IoT), machine learning, and incentive mechanism design.

HONGYANG DU (duhy@hku.hk) is an assistant professor at the Department of Electrical and Electronic Engineering, The University of Hong Kong. He received his Ph.D. degree from the College of Computing and Data Science, Energy Research Institute @ NTU, Nanyang Technological University, Singapore, in 2024. He serves as the Editor-in-Chief assistant of *IEEE Communications Surveys & Tutorials* (2022-2024), and the Guest Editor for *IEEE Vehicular Technology Magazine*. His research interests include edge intelligence, generative AI, and network management.

JIAWEN KANG (kavinkang@gdut.edu.cn) received the Ph.D. degree from the Guangdong University of Technology, China, in 2018. He has been a postdoc at Nanyang Technological University, Singapore, from 2018 to 2021. He is currently a full professor at Guangdong University of Technology, China. His research interests focus on blockchain, security, and privacy protection.

JING WU (wujing@jlu.edu.cn) received the Ph.D. degree in communication and information system from Jilin University, Changchun, China. She is a lecturer with Jilin University. Her research interests are Wireless Networks and Intelligent Learning Algorithms.

SUMEI SUN (sunsm@i2r.a-star.edu.sg) is a principal scientist, Deputy Executive Director (Research), and Head of the Communications and Networks Department at the Institute for Infocomm Research (I2R), Agency for Science, Technology, and Research (A*STAR), Singapore. She also holds a joint appointment with Singapore Institute of Technology and an adjunct appointment with the National University of Singapore, both as a full professor.

PING ZHANG (zhang@bupt.edu.cn) received the Ph.D. degree in circuits and systems from Beijing University of Posts and Telecommunications, Beijing, China, in 1990. He is currently a Professor with Beijing University of Posts and Telecommunications, the Director of the State Key Laboratory of Networking and Switching Technology and the Department of Broadband Communication of Peng Cheng Laboratory, and a member of IMT-2020 (5G) Experts Panel and Experts Panel for China's 6G Development. He was the Chief Scientist of the National Basic Research Program (973 Program), an Expert of the Information Technology Division of National High-Tech Research and Development Program (863 Program), and a member of the Consultant Committee on International Cooperation of National Natural Science Foundation of China. His research interests include wireless communication. He is an Academician of Chinese Academy of Engineering.