Intelligent Flexible Position Antenna Systems for Networking: A Survey

Intelligent Flexible Position Antenna Systems for Networking: A Survey

Xianglin Yu, Jiacheng Wang, Rose Qingyang Hu, *Fellow, IEEE*, Dong In Kim, *Life Fellow, IEEE*, Naofal Al-Dhahir, *Fellow, IEEE*, Henk Wymeersch, *Fellow, IEEE* and Nan Zhao, *Senior Member, IEEE*

***Abstract*—Flexible position antenna (FLA) is a promising technology which can reconstruct the channel mapping by adjusting the parameters of antennas such as position, pattern and polarization, thereby adapting to the time-varying environments. Such a paradigm shift in antenna technology is expected to enable next generation networks to achieve multiple enhancements in data transmission rate, latency, and connectivity density, which supports a plethora of emerging applications. However, conventional FLA systems rely on accurate mathematical models, which suffer from high computational complexity. Thus, it is difficult to adapt to the dynamic environments due to the computation delay. Thanks to its powerful feature extraction and decision-making capabilities, artificial intelligence (AI) has emerged as an effective solution to these challenges. Thus, intelligent FLA has attracted widespread academic attention. This paper provides a comprehensive review of intelligent FLA systems for networking. We first review the fundamental principle and implementation architectures of FLA, including reconfigurable antenna, movable antenna, fluid antenna and pinching antenna, and then we introduce some key AI techniques. Building on this, we discuss the motivation and advantages of introducing AI into FLA systems and investigate the applications of intelligent FLA in various types of networks. Finally, we delineate the challenges and future directions of intelligent FLA systems for networking.**

***Index Terms*—Artificial intelligence, flexible position antenna, fluid antenna, movable antenna, networking, pinching antenna, reconfigurable antenna**

I. Introduction

A. Background

With the widespread commercial application of the fifth generation mobile communications (5G), the academia and industry have begun exploring the sixth generation mobile communications (6G). As the evolution of 5G, 6G is expected to surpass 5G in terms of data transmission rates, latency, and connectivity density to support the emerging applications such as immersive communications, remote medicine and machine type communications [1], which shifts the networking paradigm from the internet of everything to the intelligent internet of everything. To achieve these goals, installing more antennas and expanding transmission bandwidth have become two main technical approaches [2]. Massive multiple-input multiple-output (MIMO) and extremely large-scale MIMO deploy a large number of antennas at the base station (BS) to achieve spatial multiplexing, thereby enhancing the network capacity and spectral efficiency [3]. In addition, by employing higher frequency bands, such as millimeter wave, terahertz, and visible light, it is attainable to deploy networks with greater bandwidth to achieve ultra-high data rates. However, the high frequency bands suffer from severe path loss and limited coverage region. Although upper mid-band frequencies from 7-24 GHz can achieve the balance between network capacity and coverage region [4], they require more antennas to provide sufficient array aperture, which increases the complexity of hardware implementation and the cost of large-scale deployment. The existing approaches still struggle to manage the trade-off between network capacity and implementation costs [5]. Therefore, it is crucial to develop new technology to increase network capacity at low cost.

Recently, the concept of flexible position antenna (FLA) has been proposed in academia [6], whose the core idea is to adjust the parameters of the transceiver antennas, including position, pattern, polarization, and even the geometry of the array to improve network performance. Compared with conventional fixed position antenna (FPA), FLA can dynamically adjust the parameters of antennas based on the environmental variations to reconstruct the channel mapping [5], [7], providing additional degrees of freedom (DoF) to network design [1]. Such a shift in antenna paradigm allows transceivers to proactively adapt to the time-varying environments, which enables more powerful spatial multiplexing with fewer antennas. It offers significant advantages in signal enhancement [8], interference mitigation [9], and wide-area coverage [10]. As a result, FLA

Manuscript received July 27, 2025; revised September 01, 2025; accepted October 21, 2025. The work of N. Zhao is supported in part by the National Natural Science Foundation of China (NSFC) under Grant U23A20271 and 62271099. The work of N. Al-Dhahir is supported by Erik Jonsson Distinguished Professorship at UT-Dallas. *(Corresponding author: Nan Zhao.)*

Xianglin Yu and Nan Zhao are with the School of Information and Communication Engineering, Dalian University of Technology, Dalian 116024, China (e-mail: 2436960712@mail.dlut.edu.cn, zhaonan@dlut.edu.cn).

Jiacheng Wang is with the School of Computer Science and Engineering, Nanyang Technological University, Singapore 639798 (e-mail: jiacheng.wang@ntu.edu.sg).

Rose Qingyang Hu is with the Department of Electrical and Computer Engineering, Utah State University, Logan, UT 84322 USA (e-mail: rose.hu@usu.edu).

Dong In Kim is with the Department of Electrical and Computer Engineering, Sungkyunkwan University, Suwon 16419, South Korea (email: dongin@skku.edu).

Naofal Al-Dhahir is with the Department of Electrical and Computer Engineering, The University of Texas at Dallas, Richardson, TX 75080 USA (e-mail: aldhahir@utdallas.edu).

Henk Wymeersch is with the Department of Electrical Engineering, Chalmers University of Technology, 41296 Gothenburg, Sweden (e-mail: henkw@chalmers.se).

[1] Antenna selection is achieved by activating a subset of antennas in a large-scale array to reconstruct the geometry of antennas. However, these antennas can only be activated at discrete positions and cannot move continuously within spatial region, and the distance between two antennas is at least half wavelength. In contrast, FLA can be adjusted flexibly in multiple dimensions, and in some cases, and it can break through the limitation of half wavelength apart, which allows the wireless network to fully exploit channel variations.

has been widely studied, leading to various implementation methods. The initial implementation of FLA can be found in reconfigurable antenna (RA) system, which reduces deployment costs by adjusting antennas' frequency, pattern, and polarization [11]. Zhu *et al.* developed a movable antenna (MA) system, which leverages the characteristics of multipath propagation via the local movement of antennas to combat small-scale fading [12]. Furthermore, Wong *et al.* proposed a fluid antenna (FA) system [13], extending the FLA concept to any software-controllable fluidic, conductive or dielectric structure to adjust its radiation characteristics. Besides, Ding *et al.* studied a pinching antenna (PA) system for indoor network [14], which emits electromagnetic wave to users by applying dielectric particles on the pre-installed waveguides, effectively tackling with the line-of-sight (LoS) blockage between transceivers [15].

However, the design of network enabled by FLA is typically a high-dimensional non-convex optimization problem, where the parameters of antennas are coupled with other optimization variables, making it difficult to be solved directly. Therefore, some optimization algorithms, such as gradient descent [16], alternative optimization (AO) [17], successive convex approximation (SCA) [18] and particle swarm optimization (PSO) [19] have been utilized to address this problem. These conventional algorithms suffer from high computational complexity and introduce significant computational time delay, which hinders the real-time adaptation to the dynamic environments and limits the application scenarios of FLA. Fortunately, artificial intelligence (AI) technologies, including deep learning (DL) [20], reinforcement learning (RL) [21] and federated learning (FL) [22], demonstrate powerful feature extraction and autonomous decision-making capabilities, which have been proven to handle complex tasks in communication network, such as channel estimation [23], beamforming [24] and resource allocation [25]. DL establishes the mapping between problem description and solution in a data-driven manner. A well-trained DL neural network can obtain the optimal solution via a single forward computation, which reduces computational complexity [26]. RL converts the problem into a markov decision process and achieves dynamic decision-making through the interaction with the environment [27]. FL interacts with model parameters rather than raw data, thereby protecting the privacy of users [28]. In addition, the hybrid optimization approach has also been explored to tackle the non-convex problem. By combining the large language model (LLM) and conventional convex techniques, it reduces the reliance on large-scale training data and enables adaptive optimization in dynamic environments [29]. Given the aforementioned advantages, adopting AI to optimize the parameters of antennas to further release the potential of FLA is considered as a promising research direction.

B. Motivation and Contribution

As an emerging technology, FLA has attracted widespread attention and inspired extensive research efforts from various perspectives. Some surveys start from the perspective of theoretical modeling, implementation approaches and application scenarios, while others investigated the optimization approaches. The comparison between the our work and relevant ones is shown in Table I. The mentioned surveys primarily focus on the fundamental model [7], [30], [31], [35], [36], [37], advantages [32], [33], [34], and hardware implementations [6], [39], [40], [41], [42]. The covered networks include integrated sensing and communication (ISAC) [43], integrated sensing, communication and computation (ISCC) [45], low-altitude wireless network [46] and multiple access network [7]. In addition, the optimization approaches have been reviewed, including conventional algorithms [5], [38] and AI-based ones [47], [48]. While insightful, the role of AI for FLA systems design is not thoroughly investigated, especially the application for dynamic environments. The range of intelligent FLA-assisted network types discussed also remains insufficiently comprehensive. Motivated by these considerations, this paper provides a comprehensive survey of intelligent FLA systems for networking. Specifically, it covers the fundamentals of FLA and AI, the role of AI in FLA systems and its applications in various networks, which provides researchers with a comprehensive understanding of AI-enabled FLA network design and inspiring future research. The main contributions of this paper are summarized as follows:

TABLE I
COMPARISON BETWEEN THE OUR WORK AND RELEVANT ONES.

Reference	Main Contribution
[5]	The fundamentals, optimization approaches, channel acquisition and prototypes of MA.
[6]	The fundamentals and advantages in channel hardening and spectrum-energy efficiency of FLA systems.
[7]	The channel models, channel estimation, fundamentals, multiple access approaches and hardware designs of FA.
[30]	The reconfigurability of RA and design approaches.
[31]	The mathematical model and possible types of FA.
[32]	The fundamentals and networking technology of FA.
[33]	The advantages of MA over FPA.
[34]	The modeling, advantages and realizations of 6DMA.
[35]	The fundamentals, design issues, applications, simplified realizations and prototypes of 6DMA.
[36]	The principles and potential system designs of PA.
[37]	The fundamentals and transmission architecture of PA.
[38]	The resource allocation algorithms for PA system.
[39]	Material-based classification of liquid antennas.
[40]	The hardware technologies of FA.
[41]	The characteristics and applications of FA.
[42]	The general architecture and implementation of MA.
[43]	The advantages of MA in ISAC.
[44]	The hardware architectures and advantages of rotatable antenna in wireless communication and sensing.
[45]	The fundamentals, design issues and solutions of rotatable antenna enabled ISCC.
[46]	The low-altitude wireless networks aided by MA.
[47]	AI enabled FA design in ISAC.
[48]	The framework of LLM enabled FA system design.
This paper	The fundamentals of FLA, the role of AI in FLA system design and application in different networks.

- This survey categorizes FLA into RA, MA, FA and PA to analyze the principle behind its enhancement of network performance, and discusses the typical hardware implementation of FLA as well as its advantages and disadvantages. Subsequently, we provide an overview of some key AI techniques, including DL, RL, and FL, aiming to help readers to understand the characteristics and applicable scenarios of various AI algorithms.

- From the perspectives of channel estimation, antenna position optimization, beamforming and parameters design for dynamic environments, we study the challenges in FLA systems, the limitations of conventional algorithms, and the motivation and advantages of adopting AI. We also summarize the relevant AI-based algorithms.
- Furthermore, we discuss the advantages of applying FLA to different networks, including multiple access network, secure transmission network, non-terrestrial network, communication and sensing network, and indoor and outdoor networks. Then, we investigate how to employ AI to release the full potential of FLA systems for networking.
- Finally, we describe the challenges of FLA systems for networking in terms of standardization issues, theoretical foundation, hardware implementation and AI for networking, and explore its potential integration with other technologies, providing valuable insights for future research directions.

C. Organization

The remainder of this survey is organized as follows. In Section II, we first provide a comprehensive overview of the fundamentals of FLA and introduce some key AI techniques. In Section III, we explain the advantages of AI-based algorithms in FLA systems, and in Section IV, we discuss how AI-based FLA can be applied to various networks. Finally, in Section V, we study the challenges and future directions of intelligent FLA systems for networking, and this survey is summarized in Section VI. For convenience, the organization structure of this survey is shown in Fig. 1, and the abbreviations throughout the survey are listed in Table II.

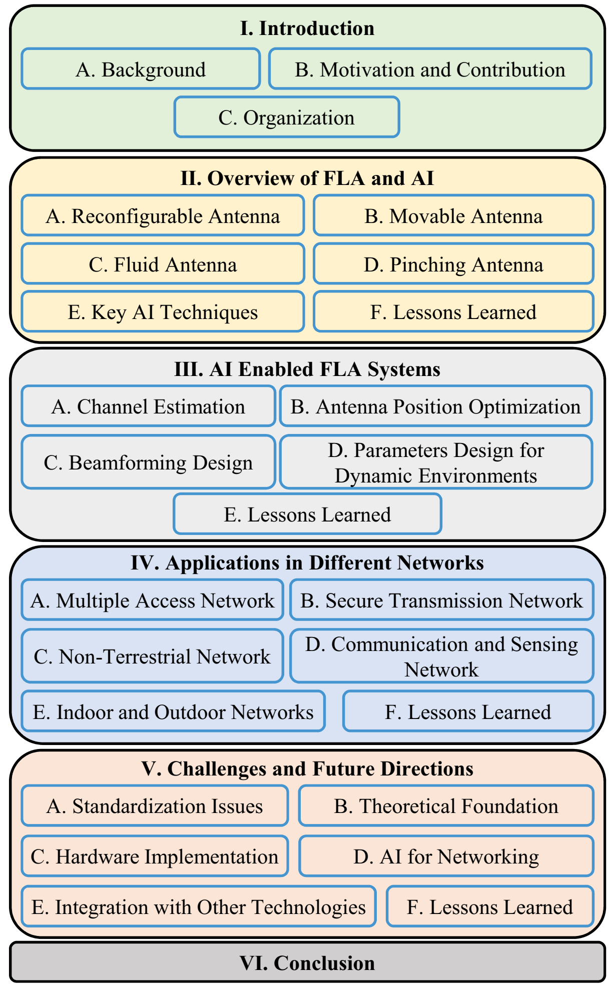


Fig. 1. The organization structure of this survey.

II. Overview of FLA and AI

In this section, we review four types of FLA, including RA, MA, FA and PA, and the comparison of their hardware prototypes is shown in Table III. Furthermore, we introduce some key AI techniques which can be employed to solve the design problem of FLA systems.

A. Reconfigurable Antenna

The concept of RA originated as early as the 1930s, initially relying on the mechanical movement of antenna components for parameters reconfiguration [54]. With the advancement of electronic technologies, since the late 1990s, the introduction of semiconductors and other novel materials has emerged as a promising approach to enhance reconfigurability [55]. Based on the type of adjustable parameters, RA can be classified into three categories [11]: frequency RA for multi-band operation [56], pattern RA for radiation direction adjustment [57], [58] and polarization RA for switching polarization states [59].

Fig. 2(a) shows an implementation of frequency RA, which achieves flexible switching of operation frequency band via changing the current distribution on the surface of the antenna [60]. It can be categorized into discrete switching and continuous tuning [61]. The former redirects the current path of antenna through the switching effect of the positive-intrinsic-negative diode, realizing the rapid switching among the preset frequency bands. The latter adjusts the voltage applied to the varactor diode to change its capacitance, achieving the smooth transition in a certain range of frequency bands [62]. Compared with traditional antenna, frequency RA can cover multiple operation frequency bands, avoiding the deployment of multiple single-band antennas and greatly reducing the complexity of the equipment. However, the electrical switches utilized in the frequency RA limit its antenna gain and radiation efficiency.

Pattern RA focuses on the spatial reallocation of the radiation power of the electromagnetic wave [58]. It is mainly based on slotted patch, parasitic antenna or metamaterial antenna to realize beamforming direction control and beamwidth reconfiguration [61]. For example, the pattern reconfigurable Yagi antenna realizes the forward and backward switching of the radiation direction by adjusting the length of the parasitic strips [57]. In [63], the leaky-wave antenna is integrated with the phased array to realize beam scanning. Based on the capability of flexible adjustment of beam direction and width of pattern

TABLE II
LIST OF ACRONYMS.

Abbreviation	Full form	Abbreviation	Full form
1DMA	One-dimensional movable antenna	GNN	Graph neural network
2DMA	Two-dimensional movable antenna	ISAC	Integrated sensing and communication
3D	Three-dimensional	ISCC	Integrated sensing, communication and computation
3DMA	Three-dimensional movable antenna	LEO	Low earth orbit
5G	Fifth generation mobile communications	LLM	Large language model
6DMA	Six-dimensional movable antenna	LoS	Line-of-sight
6G	Sixth generation mobile communications	LSTM	Long short term memory
A2C	Actor and critic	MA	Movable antenna
AI	Artificial intelligence	MAB	Multi-armed bandit
AN	Artificial noise	MIMO	Multiple-input multiple-output
AO	Alternative optimization	ML	Machine learning
AoA	Angle of arrival	MM	Majorization-minimization
AoD	Angle of departure	NOMA	Non-orthogonal multiple access
AP	Access point	OTFS	Orthogonal time-frequency space
BCD	Block coordinate descent	PA	Pinching antenna
BS	Base station	PDD	Penalty dual decomposition
CNN	Convolutional neural network	PLS	Physical layer security
CS	Compressed sensing	PPO	Proximal policy optimization
CSI	Channel state information	PSO	Particle swarm optimization
DDPG	Deep deterministic policy gradient	RA	Reconfigurable antenna
DL	Deep learning	RF	Radio frequency
DNN	Deep neural network	RIS	Reconfigurable intelligent surface
DoF	Degrees of freedom	RL	Reinforcement learning
DP	Dynamic programming	RNN	Recurrent neural network
DQN	Deep Q-network	SCA	Successive convex approximation
DRL	Deep reinforcement learning	SIC	Successive interference cancellation
FA	Fluid antenna	SINR	Signal-to-interference plus noise ratio
FAMA	Fluid antenna multiple access	SIR	Signal-to-interference ratio
FL	Federated learning	SNR	Signal-to-noise ratio
FLA	Flexible position antenna	SWIPT	Simultaneous wireless information and power transfer
FPA	Fixed position antenna	TD3	Twin delayed deep deterministic policy gradient
GAN	Generative adversarial network	UAV	Unmanned aerial vehicle

TABLE III
COMPARISON OF DIFFERENT FLA HARDWARE PROTOTYPES.

Type of FLA	Hardware prototype	Advantages	Disadvantages
RA	Switching based [49]	Simple structure	Limited adjustable flexibility
MA	Mechanical movement [50]	Enhanced flexibility in six dimensions	Large deployment physical size
FA	Liquid based [51]	High energy efficiency	Sensitive to material properties
	Pixel array [52]	Fast response speed	High implementation cost
PA	Dielectric waveguide [53]	Flexible radiation points for LoS links	Limited application in outdoor networks

RA, the BS can design the corresponding beampattern according to the requirements in different directions [64]. By aligning the mainlobe to the users and the zero point to the interference source, the interference can be significantly suppressed, which enhances the network efficiency.

Polarization RA can dynamically adjust its polarization direction, effectively addressing the multipath fading and improving the communication capacity [61]. According to the shape of polarization, the antenna's polarization can be divided into linear, elliptical and circular. Further, the linear polarization can be divided into horizontal polarization and vertical polarization, and the circular polarization can be divided into left-handed and right-handed [59]. Currently, there are many methods to realize polarization reconstruction, such as realizing linear polarization state switching based on magnetoelectric dipole antenna [65], or achieving flexible switching between linear polarization and circular polarization of cylindrical antenna through the combination of common mode and differential mode [66], which can tackle the polarization mismatch in the signal propagation process.

B. *Movable Antenna*

MA can be traced back to the Chappe telegraph system at the end of the 18th century, which realized spatial index modulation through movable arms on top of the tower, becoming the prototype of the early mechanical MA. At the beginning of the 20th century, Marconi utilized a kite to adjust the antenna position to realize the transatlantic communication [67], which verified the effect of antenna movement for performance enhancement. Later, the directional antenna was deployed on rotatable platform for dynamic beam direction adjustment [5]. In 2022, Zhu *et al.* introduced the MA into wireless communications [12], and the related optimization methods were studied to break through the limitations of FPA. Further, in 2024, six-dimensional MA (6DMA) was proposed to realize full-space flexible adjustment via three-dimensional (3D) position and 3D orientation DoF [68].

Based on the adjustable DoF, MA can be categorized into one-dimensional MA (1DMA), two-dimensional MA (2DMA), three-dimensional MA (3DMA) and 6DMA [43]. 1DMA consists of massive MA elements arranged in a one-

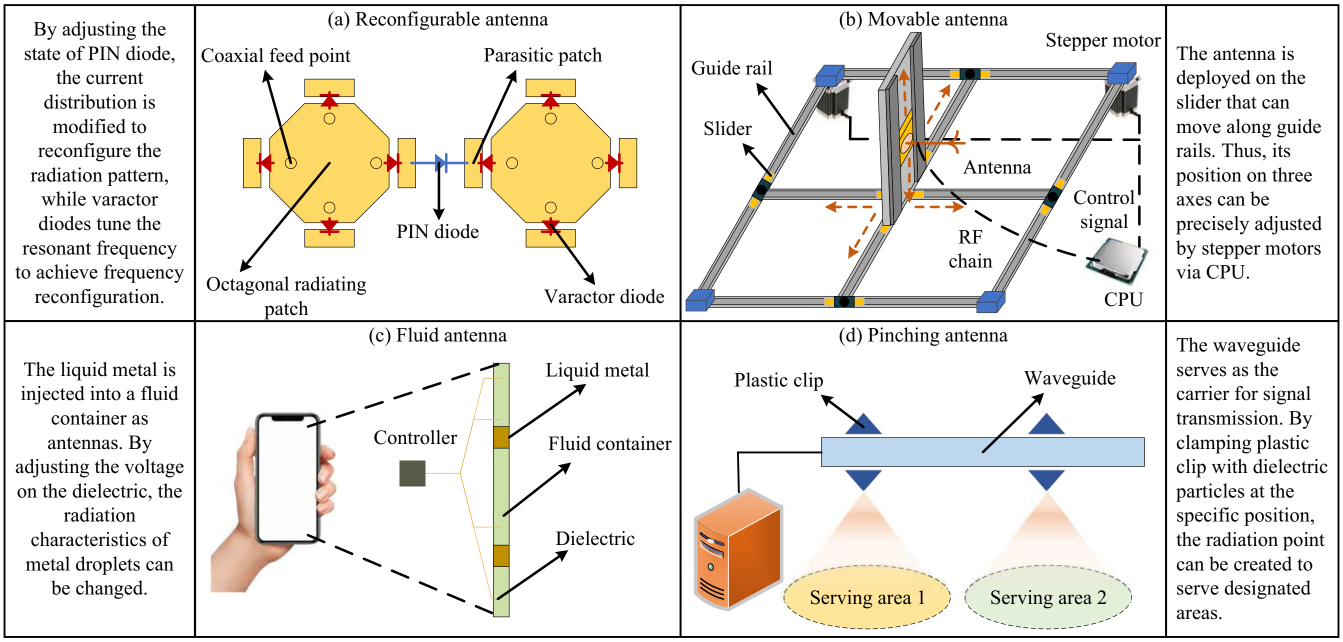


Fig. 2. The typical hardware implementation of FLA.

dimensional line segment, which is simple to implement and control. In the 2DMA system, the antenna can be adjusted in both horizontal and vertical directions, providing more flexibility. Further, the adjustable area of 3DMA is extended to 3D, which allows more precise beam control. In the multipath propagation environments, the above mentioned MA adjusts its spatial position of each antenna to realize the constructive or destructive superposition of complex coefficients of channel paths [12], thereby enhancing the signal strength or suppressing the interference. Differently, 6DMA can adjust the position of the whole antenna array. Based on the distribution of users, it dynamically adjusts the radiation pattern and polarization of the antenna, thus changing the corresponding channel gain [35].

To enable the 3D spatial flexibility of MA, a simple approach is to adjust the antenna's position by using stepper motor or micro-electromechanical system [5]. As shown in Fig. 2(b), the antenna can be deployed on a slider, which is connected to guide rails controlled by the stepper motor to adjust its position on three axes. By transforming the position coordinate information into the speed and duration of the stepper motor, the slider is driven to complete the millimeter level 3D movement, realizing the rapid and flexible 3D deployment of the antenna [42]. For 6DMA implementation, the antenna array can be deployed on retractable poles, which are equipped with motors at both ends to adjust the position and the orientation of the array [35]. The above mechanical implementation approaches have simple structure, make it easy to install and maintain with a large adjustable scale. However, the mechanical structure has a large physical size and is difficult to be deployed in device with limited space, and the response speed of mechanical movement is limited. In addition, the position adjustment of antennas requires frequent movement of mechanical components, which consumes more energy and may cause wear and tear, requiring regular maintenance [40]. Therefore, mechanical FLA is more suitable for BS or large-scale machines.

C. *Fluid Antenna*

The origin of FA can be traced back to the 1990s [39]. Inspired by the reconfigurable characteristics of liquid, the researchers began to explore the possibility of liquid antenna, realizing the dynamic parameter adjustment. In 2009, Hazem and Paul introduced the term FA, and realized the reconfiguration of the radiation pattern by manipulating the liquid dielectrics [69]. As a realization of dielectric resonant antenna, the original concept of FA is to use liquid dielectric to reconfigure the frequency, pattern or polarization. In 2020, Wong *et al.* redefined it as any software-controllable fluidic, conductive or dielectric structure which can adjust its radiation characteristics [70], and introduced the FA into the wireless communication network. Based on this concept, liquid-based and pixel-based antennas have been proposed as two paradigms [7], which are discussed as follow.

Benefiting from the flow property of the liquid, it is considered as a promising approach to enable antenna flexibility via liquid [51], which is illustrated in Fig. 2(c). The liquid metal is injected into a container as an antenna, which can be controlled by a syringe, a nano-pump or the electrowetting approach [40]. By adjusting the position, the number even the size of the metal droplets, the radiation characteristics of antenna can be flexibly changed, satisfying the specific communication requirements in real time. This durable structure enables the antenna to achieve dual enhancement in energy efficiency and reliability, and realizes fine electromagnetic control based on the high resolution adjustment of antenna's position. However, the selection of liquid materials requires the consideration of cost, stability and the corresponding electromagnetic characteristics. In addition, the antenna position adjustment speed is dominated by the liquid flow rate and is influenced by multiple factors, with typical response speed ranging from milliseconds to seconds [5]. Therefore, the liquid based implementation method has limited response speed and is suitable for scenarios which are insensitive to adjustment latency, such as low duty cycle internet of things devices and offshore platform network.

Another FA implementation approach is reconfigurable pixel antennas. It consists of massive pixels which are interconnected to each other by electronic switches such as diodes and transistors, etc [7]. The flexibility is realized by optimizing the status of each electronic switch, which can change the geometry of the pixel array and adjust the distribution of current over the array, thereby achieving the desired beam pattern and other radiation characteristics [52]. Similar to MA, it can also improve the network performance by aligning the signal phase shift associated with different propagation paths to form constructive addition or destructive subtraction [13]. Due to the millisecond level or even shorter response speed of electronic switch [6], [7], it can be reconfigured quickly and is suitable for high dynamic networks such as vehicular network and unmanned aerial vehicle (UAV) network. However, it also has some disadvantages. Aiming to exploit the spatial multiplexing capability, the wavelength level array may contain hundreds of pixels, which is difficult to realize with low cost.

D. Pinching Antenna

Although RA, MA and FA have made great progress, they typically adjust their antennas' position in the space of a few wavelengths, which can only mitigate small-scale fading caused by multipath effect, and it is difficult for them to reconstruct the LoS links to tackle with large-scale fading caused by blockage [14]. To address this issue, in 2022, DOCOMO introduced PA and proposed a demonstration to validate PA's capability of reconstructing LoS links [53]. Similar to leaky-wave antenna, PA transmits signal by using a dielectric waveguide as a carrier and radiates the electromagnetic wave at the special point. Differently, the radiation point of PA is activated via pinching dielectric particles on the waveguide, which allows it to flexibly adjust the radiation point instead of being fixed [71]. Thus, PA is considered as one of approaches to achieve FLA systems.

Fig. 2(d) shows the implementation of PA. The principle of PA relies on the coupling effect between the dielectric waveguide and the pinching element [37]. The dielectric waveguide consists of a bar-shaped dielectric with a high permittivity surrounded by a low permittivity dielectric [53]. The pinching element is a plastic clip with dielectric particles attached to its tip. As the high-frequency electromagnetic wave propagates within the waveguide, the energy is confined to the inner dielectric layer due to the higher permittivity inside than outside. When the pinching element pinches on the waveguide, an electromagnetic coupling phenomenon occurs, which transfers a portion of the energy within the waveguide to the pinching element and radiates it to the free space, thereby establishing a controlled radiation point on the waveguide [71] and reconfiguring the LoS links for the blocked users [15].

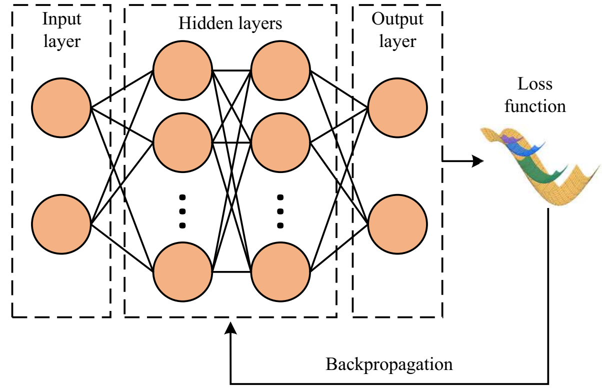


Fig. 3. The basic structure of DL.

On the other hand, even if there exist LoS links in the system, the performance of the network can be further improved by PA [36]. Since PA has a larger aperture, the users are usually located in the near-field region [37]. By deploying PA in the neighboring position of users, the distance between the users and the transmitter can be significantly shortened, which constructs the stronger and stable LoS links. In addition, since the symbols transmitted on the same waveguide are identical, its radiation amplitude and phase are related to the specific position of the PA, which brings an additional DoF for network optimization, called pinching beamforming [71]. By optimizing the position of the PA, the signal received by the users can be enhanced and the interference between users can be suppressed, which improves the quality of service [72]. Despite the cost-effective and scalable implementation of PA, the adjustment of its position relies on manual intervention, which is difficult to automate in response to variation of channel state information (CSI). On the other hand, the waveguide needs to be pre-installed in the suitable position to activate radiation point near the users. Therefore, PA is suitable for indoor network.

E. Key AI Techniques

Thanks to the outstanding feature extraction and decision-making capabilities, and the proliferation of wireless datasets, AI has become a promising method for network design. By transforming from model-driven to data-driven, the complexity of network design has been significantly reduced. Therefore, this subsection provides an overview of some key AI techniques as follows.

1) Deep Learning: As shown in Fig. 3, DL realizes various kinds of functionalities through neural network, which consists of three parts: input layer, hidden layers and output layer [26]. The input layer is fed with original data from nature, e.g., received signal at BS, or with artificially preprocessed data, such as the distribution of users. The hidden layer is usually composed of multiple layers of neural network, which have different sizes connected in series to extract features of different dimensions, and implicitly express the correlation between different features. The output layer outputs the corresponding results according to the task of the DL model and the extracted features. In each round of training [73], the

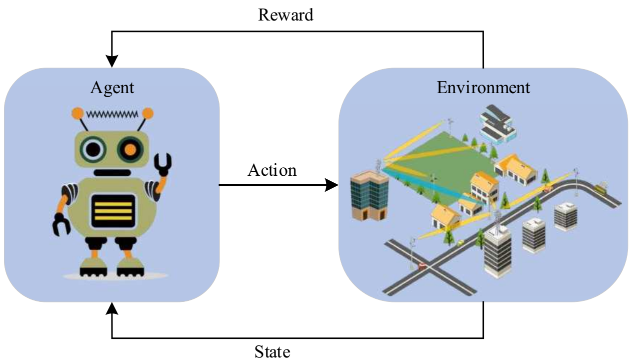


Fig. 4. The interaction between agent and environment.

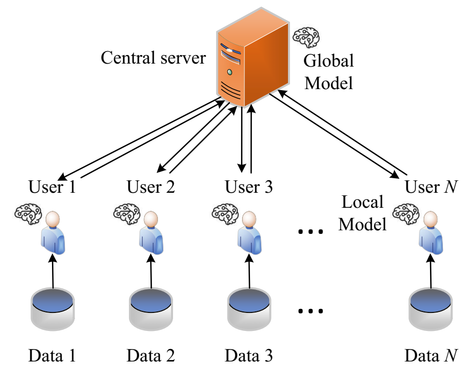


Fig. 5. The general framework of FL.

neural network's weights and bias of each layer are optimized based on backpropagation to minimize the loss function via supervised or unsupervised learning manner. Although DL requires large amounts of data and has high computational complexity in the training stage, the inference stage only needs a single forward calculation, which significantly reduces computational complexity.

Convolutional neural network (CNN) and recurrent neural network (RNN) are two widely adopted DL models. CNN is composed of convolutional layers, activation layers, pooling layers and fully connected layers [74], which is suitable for dealing with spatially correlated tasks. In the convolutional layers, the spatial correlation is extracted by a sliding kernel, and the complexity of model is reduced based on the parameter sharing mechanism. Subsequently, non-linearity is introduced in the activation layers to enhance the expression capability of the DL model. The pooling layers down-sample the extracted features, convert the low-dimensional features to the high-dimensional features, and input them into the fully connected layers to output the decision. RNN is superior to dealing with the temporal related tasks. The long short term memory (LSTM) network is a typical RNN, which consists of an input gate, a hidden gate, and an output gate. The input gate determines which features are added to the memory cell, the forget gate determines which features should be discarded from the memory cell, and the output gate calculates the current output based on the memory cell [75]. The LSTM network implicitly passes the temporal dependencies to future time steps through the memory cell via the gating mechanism, making the prediction of beamforming and CSI possible [76]. Recently, a DL model called Transformer has been proposed, which employs attention mechanism to extract dependencies between arbitrary positions in a sequence [77]. Therefore, compared with RNN, Transformer is more effective at capturing long-term dependencies and has a wider range of applications.

2) Reinforcement Learning: RL is mainly composed of agent, environment and reward. Specifically, the agent represents a machine which senses the state of the environment and makes the action based on it [27]. The environment refers to the external system that interacts with the agent, which can be changed dynamically according to the agent's action. The reward is a signal generated based on the agent's action, which measures the quality of the agent's action in the round. As illustrated in Fig. 4, in each round of interaction, the agent gives an action for the current round based on the state of the environment, and the environment generates the reward signal and feeds the reward and the state of the next round back to the agent [78]. Different from the DL which focuses on finding a model to minimize the loss function, RL explores a strategy to maximize the expectation of the reward through multiple rounds of interaction between the agent and the environment.

The advantage of RL is to solve the sequential decision-making problem [79]. It generates the empirical data through interaction between agent and the environment, and updates the strategy and the parameters of model based on it. Consequently, RL can be widely used in the scenarios of dynamic environments, multi-step decision-making, and insufficient training data. Conventional RL algorithms mainly include temporal difference and dynamic programming (DP), and DP can be further divided into two algorithms: policy iteration and value iteration. However, these algorithms have limited performance when dealing with high-dimensional continuous state or action space tasks, and it is difficult to tackle with complex scenarios [76]. Based on the powerful function fitting capability of deep neural network (DNN), deep reinforcement learning (DRL) can better express the requirements of complex scenarios, which promotes the emergence and development of DRL algorithms, such as deep Q-network (DQN), proximal policy optimization (PPO) and deep deterministic policy gradient (DDPG). These algorithms can describe more complex network models and tasks [80], thereby realizing the network optimization in the dynamic environments.

3) Federated Learning: The growing amount of data has significantly boosted the development of AI. However, most of the data exists in the form of silos, which is prohibited from being collected [81]. On the other hand, data privacy and security is also a problem. In 2016, Google first proposed the concept of FL [82], whose primary idea is to construct machine learning (ML) model based on the datasets distributed among multiple devices. FL is essentially a distributed ML technique, where each user in the network uploads the parameters of its local model rather than the local dataset, thereby reducing the requirement for centralized data. Thus, it is suitable for scenarios where local data privacy must be protected.

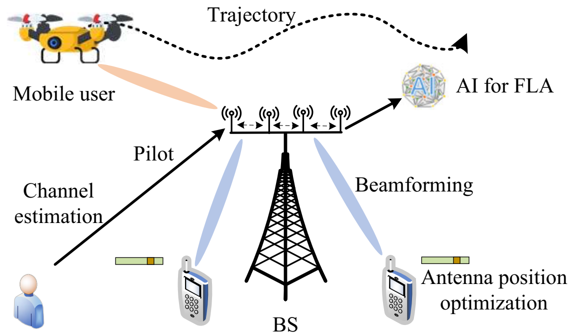


Fig. 6. Application of AI for FLA systems design.

The general framework of FL is shown in Fig. 5, which consists of multiple users with data and a central server. The training process of FL can be divided into four steps [28], [83]. First, the central server establishes the basic model and sends the structure and parameters of the model to the users. Second, the users train the model with local data and upload the parameters of the trained local model to the central server. Then, the central server aggregates the local model parameters uploaded by each user, and constructs a more accurate global model. Finally, the central server sends the updated global model parameters to users, which will be utilized to update users' local model. After several iterations, the performance of global model can be significantly improved.

F. Lessons Learned

In this section, we introduce four types of FLA from the perspectives of historical origins, hardware implementation, and performance improvement mechanisms, and compares the advantages and disadvantages of several prototypes in Table III. In addition, we review some AI techniques, including DL, RL and FL, and discuss their characteristics and applicable scenarios. The advancement of FLA enables antenna to be adjusted in multiple dimensions flexibly, which enhances the ability of transceivers to adapt to the wireless propagation environments. Different FLA implementation approaches have different characteristics in terms of response speed, resolution and adjustable dimensions, allowing flexible selection according to the application scenario. The AI algorithms can significantly reduce computational complexity via a data-driven approach and can tackle with more complex scenarios such as dynamic environments.

III. AI Enabled FLA Systems

As shown in Fig. 6, AI facilitates various aspects of FLA systems design, including channel estimation, antenna position optimization, beamforming design, and parameters design for dynamic environments. In this section, we overview the role of AI in FLA systems, highlighting its potential to enhance the adaptability of FLA systems.

A. Channel Estimation

FLA allows the network to optimize the position of antenna, bringing additional DoF for network design. These advantages rely on the perfect CSI at all positions. However, channel estimation for FLA systems is challenging. Due to its flexibility and high spatial resolution originating from continuous movement antenna or dense pixel array, the dimension of channel estimation increases dramatically. On the other hand, the number of radio frequency (RF) chains is much smaller than the number of ports, thus multiple estimations are required to obtain full CSI, which imposes a significant pilot overhead and feedback delay. The channel estimation methods developed for conventional FPA system cannot tackle with variable antennas' position.

To address the above challenges, it is necessary to develop low overhead methods to estimate the full CSI with partial observations. The conventional channel estimation approaches for FLA systems can be divided into model-based approach and model-free one. The model-based approach employs compressed sensing (CS) to reconstruct the full CSI by estimating the field response information from limited observations [84]. This approach relies on the assumption of channel sparsity, which can be violated with dense scatterers in the multipath environments. In addition, the complexity of CS-based algorithms increase significantly with channel dimension [85]. The model-free channel estimation approaches rely on the correlation between channels. Based on the linear minimum mean square error, [86] estimates the channel by exploiting the strong spatial correlation between neighboring ports, which effectively reduces signaling overhead. However, this method relies on the efficient establishment of the correlation function [87], and it can only obtain the channel of discrete ports.

Benefiting from its powerful capabilities in feature extraction [88], AI has attracted great attention in channel estimation for FLA systems. By learning the correlation between ports, [89] and [87] estimated the channel gain of other FLA ports via limited observations. The former utilized conventional LSTM network, while the latter designed multiple sub-networks for different correlation conditions, which can adjust the number of the required ports and reduce 17% overhead compared to a single network. Wang *et al.* proposed a masked autoencoder composed of an encoder and a decoder for FLA channel estimation [21]. The encoder is employed to learn the latent features of the observation ports, and the decoder integrates the latent features with masked tokens to reconstruct the full CSI. Zhang *et al.* adopted a similar autoencoder structure [90]. Differently, they introduced graph attention in the decoder and improved the generalization capability in different FLA systems via the local diffusion mechanism. By only 5% observations, it can reconstruct the full CSI with a normalized mean square error (MSE) less than 10^{-5}. Jang and Lee found that the decomposition of received pilot is similar to neural network operations, where a specific function is applied after matrix multiplication [91]. Therefore, they constructed an initial layer and an angle estimation function. In the inference stage, the position of antennas is adjusted so that the received pilot is the same as the output of the initial layer, thereby roughly estimating the angle information. Subsequently, the angle information is refined by alternating minimization, which can be utilized to derive the channel gain and obtain the CSI. Tang *et al.* designed a lightweight diffusion model based on

U-Net [23]. By taking the noisy channel and time step as the input, the diffusion model can effectively extract the spatial correlation of FLA channels for CSI reconstruction. During the stage of online inference, they adopted a skipped sampling strategy to reconstruct CSI from posterior sampling, which significantly reduces computation time while guaranteeing the performance of channel estimation.

On the other hand, thanks to the fine-tuning of pre-trained LLM, AI can effectively predict future CSI. Zhang *et al.* employed the low-rank adaption fine-tuning technique to retrain the parameters of the self-attention in GPT-2, which reduces the computational resources required for FLA channel estimation [92]. After normalizing the historical CSI and extracting temporal features via the multi-head attention mechanism, the processed data can be fed into the LLM to predict the future CSI. Yang *et al.* studied the channel prediction problem in the orthogonal time-frequency space (OTFS) scenario enabled by FLA [93]. Differently, they did not utilize the LLM to predict the future CSI directly, but to predict the low dimensional features of future channel and reconstruct the CSI based on them. In addition, to reduce the redundancy of input data, they first selected the reference port to eliminate spatial redundancy, and then the separable principal component analysis was performed to exploit the features in the spatial and delayed-doppler domains, which reduces the input size by 99%.

B. Antenna Position Optimization

FLA can fully exploit spatial DoF by adjusting the position of antennas, thereby enhancing the channel quality and network capacity. Based on the precision of antenna movement control, antenna position optimization can be divided into two types: discrete port selection and continuous position optimization.

1) Port Selection: Port selection refers to selecting a portion of positions from the predefined candidate positions to activate antennas. Specifically, the network typically evaluates the performance for each candidate position based on the channel estimation results, thereby selecting the combination of positions with the most advantageous performance. A simple approach is exhaustive search, which compares the performance of each combination to select the optimal one. It has exponential complexity [94], making it prohibitively expensive. Therefore, Zhang *et al.* [95] and Mao *et al.*[96] proposed an AO algorithm based on the semidefinite relaxation, which reduces the complexity significantly. However, the optimization process becomes complex when there are a large number of ports.

In contrast, AI can learn the internal relationship between the performance gain and the port selection strategy via a data-driven approach. Furthermore, instead of relying on AO or traversal, AI-based algorithms achieve efficient port selection through a single forward calculation. Chai *et al.* studied the port selection strategy under different spatial correlation parameters [89], [97]. They modeled the observed channel gain as a time series and utilized the LSTM network to predict the channel gain of the remaining ports, thereby selecting the optimal port. In addition, they pointed out that the network output should focus on whether the optimal port is selected rather than the accurate prediction of channel gain, which would further improve the selection accuracy. Inspired by [89], Eskandari *et al.* utilized conditional generative adversarial network (GAN) to learn the relationship between ports and signal-to-interference plus noise ratio (SINR), thereby realizing port selection based on the limited observations [98]. Compared to LSTM, this approach achieves better port selection over a larger adjustable range. Zou *et al.* proposed a port selection strategy based on multi-armed bandit (MAB) [99]. Specifically, they considered the users and ports as bandit players and arms, respectively, with the signal-to-interference ratio (SIR) of the selected port as the reward. It can select the port based on the historical performance without the need for global CSI, which significantly reduces the computational overhead. Wang *et al.* studied the multi-port selection problem based on the pointer network [21]. To overcome the limited generalization capability via the supervised learning, they utilized the pointer network as the policy function and adopted the actor and critic (A2C) algorithm to optimize the pointer network parameters in an unsupervised manner, enabling it to select ports efficiently under the different channel conditions.

2) Position Optimization: In position optimization, antennas are not limited to the predefined candidate positions, they can be flexibly deployed in continuous region. Therefore, they can better reconstruct channel mapping and improve network capacity. In the optimization problem, the coordinates of antennas are considered as optimization variables, with the objective function based on performance metrics such as users' achievable rate. However, it is non-convex and difficult to solve directly. Thus, Xiao *et al.* proposed a PSO algorithm to iteratively update the antenna position vector [19]. To maximize the channel capacity, Ma *et al.* employed SCA to optimize the position of transmit and receive antennas [100]. Hu *et al.* found the local optimal solution for the antennas' position via a gradient descent algorithm [16], thereby minimizing the transmission power.

The non-convex optimization problem has multiple local optimums. Conventional methods are sensitive to the initial point, making it easy to get stuck in low-quality local optima. In comparison, AI does not rely on the assumption of local convexity and has more powerful global exploration capabilities. Xu *et al.* modeled the position optimization problem as a sequence-to-sequence task [72], and utilized Transformer to learn the dependencies between the position of antennas and the distribution of users. They pointed that this method improves network throughput by over 30% compared to majorization-minimization (MM) and penalty dual decomposition (PDD). He *et al.* investigated graph neural network (GNN) based position optimization [101], which employed the angle of departure (AoD) as the input and output a set of auxiliary variables to obtain the optimal position under the constraint of minimum distance between adjacent antennas. Furthermore, Guo *et al.* demonstrated that the GNN can still effectively optimize the position of antennas at larger spatial scale [102]. Khisa *et al.* proposed a gradient-based meta-learning optimization algorithm [103], consisting of three layers: inner layer, outer layer, and epoch iteration, which are utilized for updating antennas' position, evaluating optimization results, and updating the parameters of neural network, respectively. It optimizes the position of antennas in a model-driven manner, avoiding complex pre-training. For imperfect CSI, Weng *et al.* proposed a heterogeneous multi-agent DDPG algorithm [104], which models the transmitter and each receiver as agents, with the velocities of antennas as the action. It can optimize the movement strategy of transceiver's antennas and enhance the sum rate of the network significantly.

C. Beamforming Design

Despite some advanced antenna technologies such as active phased array can also design beamforming, the position of these antennas is fixed [5]. In contrast, FLA can achieve more flexible beamforming by adjusting the position of antennas, which provides significant advantages such as signal enhancement, interference mitigation, and wide-area coverage.

1) Signal Enhancement: Compared to FPA, FLA can achieve more precise beamforming and focus more energy onto the receiver under the LoS link. Even in the complex multipath environments, the receiver can flexibly adjust the receive beamforming to align the signal phase shift from different paths, thereby enhancing the signal strength. Ye *et al.* proposed an AO algorithm [8], which derives a closed-form solution for beamforming based on the statistical CSI to improve the achievable rate. However, it suffers from high computational complexity. Fortunately, it has been proved that applying DL and RL to beamforming design can reduce the computational complexity while enhancing the signal strength. Xie *et al.* leveraged the powerful mapping capabilities of DL to design a flexible beamforming framework based on CNN [105]. They input the CSI to extract channel spatial information and employed narrowing convolutional model continuously to remove redundant features. Finally, all features are integrated to output the optimal 2D position of antennas and the beamforming vector. Thus, the additional DoF provided by FLA can be fully utilized to enhance the signal strength with low computational complexity.

2) Interference Mitigation: FLA can alleviate clutter and the interference between users. The transmitter can suppress sidelobe based on the flexible beamforming. On the other hand, the receiver can construct null beam in the direction of the interference source, which improves the anti-interference capability of the received signal. For the interference from undesired directions, Zhu *et al.* jointly optimized the position of antennas and beamforming [9], ensuring that the steering vectors for the undesired directions are orthogonal to those for the desired direction. The simulation result shows that FLA can achieve beam nulling in three undesired directions and full array gain in the desired direction simultaneously. In contrast, FPA suffers a gain loss of 87.5% in the desired direction. Tang *et al.* also considered the scenario where the network has multiple interference sources [106]. To reduce the computational complexity, they adopted a DL-based framework. By utilizing the angle of arrival (AoA) as the input, the position of antennas and beamforming are optimized alternately to maximize the SINR of received signal. He *et al.* proposed a GNN-based framework [24], which utilized the interference channel as the input to optimize the beamforming vector and power allocation. Although it does not employ FLA, it can adapt to the number of transceiver pairs, providing insights for enhancing the scalability of FLA beamforming based on DL.

3) Wide-area Coverage: Thanks to the adjustable position of antennas, the BS can flexibly adjust the beam shape and direction, which can enhance the beamforming gain in multiple desired directions and realize wide area coverage. Ma *et al.* employed SCA algorithm to derive the beamforming vector iteratively [10]. It can be converted into a quadratically constrained quadratic program problem, whose computational complexity is cubic in the number of antennas, leading to high computational overhead. In comparison, a well-trained neural network can avoid matrix inversion and decomposition, significantly reducing computational complexity. Kang proposed a DL-based scheme to learn the mapping between the AoD and multi-beamforming in an unsupervised manner [20]. Its computational complexity is only quadratic in the number of antennas, which reduces the complexity by one order of magnitude compared to SCA. Wang *et al.* designed DL-based multi-beamforming under more constraints [21]. To avoid penalty term in the loss function which degrades the quality of solution, they constructed a Lagrange dual function to train the neural network. Then, the multi-beamforming is indirectly obtained by optimizing the Lagrange multipliers and network parameters alternately.

D. Parameters Design for Dynamic Environments

As the requirements of users and environmental conditions change, the design of FLA faces more severe challenges. In the dynamic environments, the paths of signal propagation and the position of users are constantly varying, making CSI estimation extremely difficult and full of uncertainty. Thus, it is difficult to dynamically adjust antenna parameters based on the real-time CSI to ensure the quality of service. To address this problem, Zhu *et al.* proposed a scheme to jointly optimize the position of antennas and beamforming over time [17]. They converted the decision-making process into a discrete sequential optimization problem, and utilized an AO algorithm to obtain the local optimal solution which satisfies the requirement of time-varying coverage region. In addition, they pointed out that the position of antennas can be optimized at the beginning of each time slot, and remain fixed until the requirement of coverage region changes, which can further reduce the computational complexity. On the other hand, some approaches can also be employed to avoid relying on the perfect instantaneous CSI. Ma *et al.* considered the imperfect CSI with norm-bounded and randomly distributed errors, and constructed a directed weighted graph to convert the optimization problem into a shortest path problem, which can be solved via dynamic programming algorithms [107]. Chen *et al.* designed the parameters of antennas based on the statistical CSI [108], and adopted a constrained stochastic SCA to maximize the expected value of the achievable rate.

However, the complexity of the above algorithms is high, which makes the time delay become a challenge. Due to the frequent CSI estimation and the adjustment of antenna parameters in the dynamic environments, the high time delay will significantly affect the quality of service in real-time. Although [17] has proposed a scheme to reduce complexity, it does not take full advantage of FLA to adapt to the dynamic environments. To tackle the time-varying CSI, Feng *et al.* proposed a block successive upper bound minimization algorithm to optimize the parameters of antennas iteratively [109], and designed a deep unfolding network to avoid matrix inversion, which accelerates convergence and reduces the computational latency. Xie *et al.* employed a graph attention network based approach to jointly optimize the beamforming and the position of antennas with millisecond level inference speed, which meets the requirement of real-time communication [110].

RL can also handle the complex non-convex constraints. In addition, it can interact with the environment to select the optimal action based on the state, which enables it to adjust strategy in real time [111]. Therefore, RL has attracted widespread attention to design the parameters of FLA in the dynamic environments. Zhao *et al.* proposed an antenna mode selection scheme based on the MAB [112]. To adapt to the time-varying channel, they employed a sliding window to reduce the influence of outdated information, thereby tracking the optimal antenna mode and enhancing the capacity of network. Dai *et al.* considered the coordinates of antennas as the action space and introduced spectral efficiency into the state space [113]. Then, the PPO algorithm is adopted to optimize antenna position with low computational complexity to compensate for doppler shift caused by high speed movement. Similarly, Ahmadzadeh *et al.* converted the non-convex optimization problem into a markov decision process [22], and employed the twin delayed deep deterministic policy gradient (TD3) algorithm for real-time decision-making in the dynamic environments. Waqar *et al.* utilized multi-agent RL to select the optimal port and design scheduling strategy [114]. Each user is modeled as an agent which can adjust its action based on the local state. Thus, the dimension of the agents' action and state space is independent of the number of users and the size of network. Besides, a derivative network is introduced into the reward function, allowing agents to optimize the parameters of the RL network based on the immediate reward and future trend, which enhances its adaptability.

E. Lessons Learned

Although FLA brings additional DoF to the network design, the flexibility of antennas significantly increases the dimensionality of channel estimation. On the other hand, the adjustable antenna position enhances signal quality and coverage. However, the coupling between the position of antennas and beamforming makes conventional algorithms computationally intensive. In the dynamic environments, the position of antennas and beamforming need to be adjusted in real-time to adapt to the environments. The computational delay caused by high complexity algorithms is intolerable. AI techniques have the remarkable capability to deal with nonlinear problems, and can extract features in multiple dimensions autonomously for FLA system design, which can reduce the computational complexity significantly. In the future, AI will possess more powerful comprehension capability, and it is expected to solve multiple FLA system design problems via a single model.

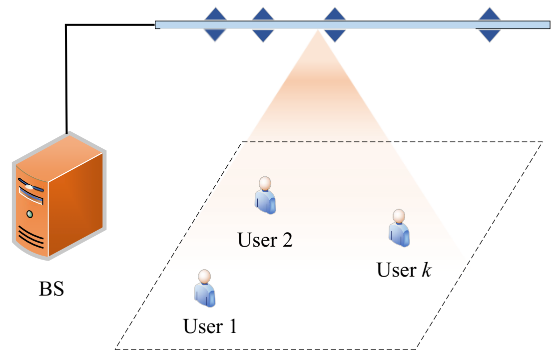


Fig. 7. Application of FLA in NOMA network.

IV. Applications in Different Networks

Thanks to the flexible antenna position and beamforming, network can further improve throughput and expand coverage region of service. In this section, we review the application of FLA in different types of network, including multiple access network, secure transmission network, non-terrestrial network, communication and sensing network, and indoor and outdoor networks.

A. Multiple Access Network

1) Non-orthogonal Multiple Access (NOMA): Unlike orthogonal multiple access, NOMA allows multiple users to share the same time-frequency resource. The transmitter allocates different power to each user and broadcasts to them in a superimposed manner. The users first rank the signals based on their strength, then utilize successive interference cancellation (SIC) to decode the signal of each user and eliminate multi-access interference progressively. NOMA can achieve multiplexing in the power domain, enhancing the spectrum efficiency of the network [115]. As shown in Fig. 7, PA feeds the superimposed signal of all users on a waveguide, which is highly compatible with NOMA. Zhou *et al.* studied how to incorporate PA with NOMA [116]. To maximize the sum rate, they alternately optimized the position of antennas and power allocation, where the power allocation is derived via the Karush-Kuhn-Tucker condition, and the position of antennas is determined by a binary search approach. On the other hand, FLA can change the channel quality for each user, which enables the transmitter to allocate power more flexibly, including power level and decoding order. Zhou *et al.* investigated the application of NOMA in the multiple-input single-output system, where each user is equipped with a single FLA [18]. Based on the far-field response model, they illustrated the relationship between power allocation coefficient and channel characteristics, and utilized SCA to derive the position of antennas for channel capacity maximization. To increase the number of active users, Han *et al.* proposed a multi-agent RL algorithm based on DQN, which makes it

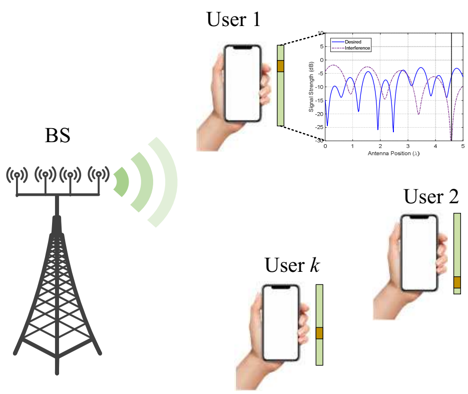


Fig. 8. Multiple access enabled by FA.

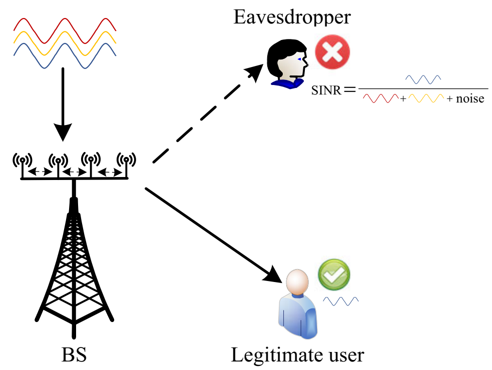


Fig. 9. Adopting FLA in PLS network.

possible for each user to select a subchannel and allocate power based on their CSI in real time [117]. It inspires the employment of AI to design FLA-assisted NOMA network. DL can predict CSI based on the historical information, thereby adjusting the position of antennas in advance to reconstruct the channel mapping. Furthermore, the transmitter can intelligently allocate power based on the predicted CSI. The overall process can be integrated into a neural network to output the optimal strategy in an end-to-end manner, which has low computational complexity, thereby adapting to the complex and time-varying environments.

2) Fluid Antenna Multiple Access (FAMA): Fig. 8 shows a typical FAMA system model. Taking the user 1 as an example, the receiving antenna can be adjusted within a range of 5λ, where λ is the wavelength. It can be observed that the strength of the desired signal and the interference signal fluctuates with the position of antenna. By deploying the antenna at the deep fading point of the interference signal, the interference between users can be suppressed, thereby maximizing the SIR of the user. The essence of FAMA is to utilize the fading phenomenon of interference signal to achieve multiple access without the collaboration between the transmitters and receivers. Compared with NOMA, FAMA can access more users without complex SIC operation and the knowledge of interference CSI in advance. Therefore, it is considered as a promising multiple access technology. Wong and Tong studied FAMA network in [13]. They assumed that the user can select port based on the deep fading point of interference signal symbol by symbol. However, it switches port frequently and is difficult to realize. To make FAMA possible, Wong *et al.* indicated that the selected port can remain unchanged until the fading channel changes, which can still reduces the outage probability [118]. The aforementioned schemes require users to obtain their own CSI in real time. In the complex propagation environments, the fading envelopes and CSI vary randomly. Thus, the users need to traverse all ports to find the deep fading point of the interference signal, resulting in high computational complexity. AI can learn the implicit characteristics of interference variation and select port with low computational complexity. Therefore, some researchers have employed AI for port selection to further liberate the potential of FAMA. Waqar *et al.* utilized a bidirectional LSTM network to learn the mapping between the observed ports and the SINR of the remaining ports, avoiding the requirement of prior knowledge of CSI for all ports [119]. Eskandari *et al.* achieved FAMA via the GAN-based port selection strategy [98]. Compared to LSTM, it has a lower outage probability. In addition, Waqar *et al.* further studied the FAMA assisted by RL, where each user is considered as an agent [114]. The users can interact with the environment to assess their channel state, and decide whether to access the network via FAMA autonomously.

B. Secure Transmission Network

1) Physical Layer Security (PLS): Due to the broadcast and openness nature of wireless channels, the unauthorized devices may also receive signal carrying confidential information. PLS ensures the secure transmission by maximizing the difference between legitimate channel and eavesdropping one [120]. As shown in Fig. 9, a typical secure transmission network via PLS consists of a BS, a legitimate user, and an eavesdropper. By introducing artificial noise (AN) into the signal and optimizing the beamforming, the BS can enhance the strength of the desired signal received by the user and suppress the signal quality of the eavesdropper. FLA can adjust the position of antennas to change the correlation between the legitimate channel and the eavesdropper one [121], which further improves the secrecy performance against eavesdroppers. However, the eavesdropping capability of FLA-enhanced eavesdroppers will also be enhanced. To this end, the BS needs to adjust the transmit signal to make the eavesdropper at the deep fading point of the confidential information envelope. In addition, flexible beamforming can more accurately control the beam direction, which further enhances the beam gain towards legitimate users. Tang *et al.* studied MIMO system assisted by FLA [122]. Aiming to maximize the secrecy rate, they jointly optimized the position of antennas, transmit precoding and AN via block coordinate descent (BCD) and MM methods. It assumes that the BS can obtain perfect CSI based on the field response model. If there are errors in the estimated AoD and path response matrix, it will impact the security of the network severely. Furthermore, it is only applicable to a single time slot and struggles to address the time-varying CSI in practical scenarios. Thanks to the ability to interact with the

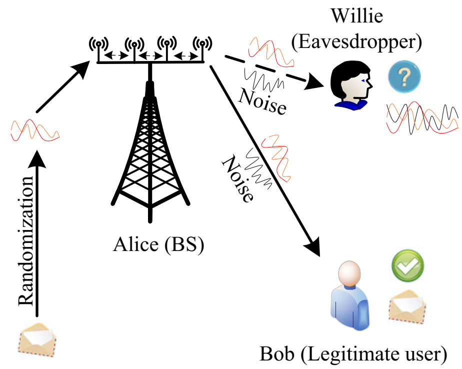


Fig. 10. Utilization of FLA in covert communication network.

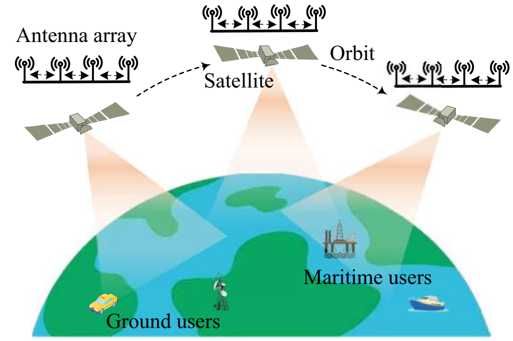


Fig. 11. The model of satellite network assisted by FLA.

environment, DRL can implicitly obtain the environmental information via DNN and output optimal strategy to overcome the limitations of conventional algorithms. Hung *et al.* employed the PPO algorithm to jointly optimize the position of antennas and transmit beamforming [123]. The PPO algorithm interacts with the environment through the exploration and exploitation mechanism to adapt to channel variation. Even if the estimated CSI of eavesdropper is imperfect, it can still explore robust beamforming to ensure the secure transmission.

2) Covert Communication: Unlike PLS, which suppresses the decoding rate of eavesdropper, the purpose of covert communication is to prevent eavesdropper from determining whether the legitimate user is transmitting [124]. As shown in Fig. 10, covert communication randomizes the transmitted information and embeds it in noise during propagation, which introduces uncertainty and reduces the probability of detection by eavesdropper. Therefore, from the perspective of signal detection, covert communication utilizes a variety of methods to increase uncertainty for eavesdropper and reduce uncertainty for legitimate user, thereby achieving the secure transmission of confidential information. In FLA systems, the PA can adjust the large-scale fading, while the MA and FA can adjust small-scale fading. Thus, FLA can introduce more uncertainty into the channel. In [125], Jiang *et al.* utilize the PA to establish LoS link for legitimate user. Even if the eavesdropper has better channel condition than the legitimate user, covert communication can still be achieved by optimizing the position of antennas. Thanks to the additional DoF provided by MA, Mao *et al.* jointly optimized position of antennas and transmit beamforming to reduce the signal strength of eavesdropper [126]. Therefore, it is difficult for eavesdroppers to detect users' communication behavior in the presence of noise uncertainty. The aforementioned methods assume that the antennas can be immediately deployed at the optimal position, whereas in the practical scenarios, it requires time to adjust the position of antennas. Therefore, Xie *et al.* studied how to optimize the trajectory of FLA within the constrained region [127]. Specifically, they modeled the movement of FLA as a markov decision process and adopted the DQN algorithm to design their trajectories, where the auxiliary rewards are introduced in the reward function to improve exploration efficiency. It can coordinate the movement of multiple antennas, significantly improving covert rate and ensuring secure transmission.

C. Non-Terrestrial Network

1) Satellite Network: With the development of the space industry and increasing demand for communications, more and more researchers focus on satellite communication. Due to the coverage of signal on the surface of the earth, it can provide all-weather service to regions such as oceans and mountains. Although satellite network has a wide coverage area, the communication link between satellite and ground node has long propagation distance and high path loss, and is easily affected by multiple factors such as the atmosphere [128]. As shown in Fig. 11, FLA introduces additional DoF. By adjusting the position of antennas, the satellite can flexibly design the beamforming to enhance beam gain in the desired direction and overcome large-scale fading. Zhu *et al.* applied FLA to low earth orbit (LEO) satellite network, and jointly optimized the position of antennas and beamforming through a SCA algorithm to achieve dynamic beam coverage and interference mitigation [17]. For full-duplex satellite communication, Lin *et al.* employed FLA to suppress self-interference, and proposed a two-loop PSO algorithm to reduce transmit power [129]. On the other hand, medium earth orbit and LEO satellites move at the high speed relative to the ground, which results in the rapid variations in channel. Concurrently, researchers adopt frequent channel estimation to overcome outdated CSI, or design satellite network directly based on the imperfect CSI, leading to performance degradation. Fortunately, AI can predict future CSI based on the historical channel characteristics, providing a solution to enhance the timeliness of CSI [130]. Yang *et al.* studied OTFS-enabled satellite communication network [93]. To adapt to the dynamic link and overcome the time overhead associated with adjusting the position of antennas, they employed LLM to predict future CSI one frame in advance. Based on the channel characteristics of the past 20 time slots, the prediction results of LLM approach perfect CSI, which significantly improves channel capacity and spectral efficiency.

2) Air-ground Network: Benefiting from its flexibility and cost-effectiveness, aerial platform such as UAV has been developed rapidly, which is combined with ground infrastructure to form air-ground network [131]. As shown in Fig. 12, compared to the satellite network, it has lower flight altitude and propagation delay. However, during the movement of the aerial platform, the channel between the aerial platform and

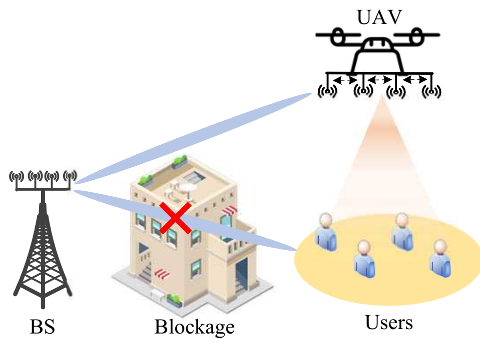


Fig. 12. Integration of FLA in the air-ground network.

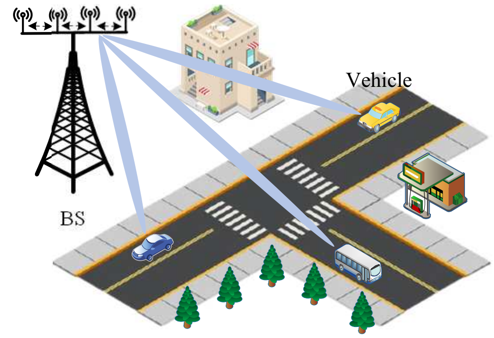


Fig. 13. Implementation of FLA for vehicular communications.

ground node is changing rapidly. The aerial platform equipped with FLA can adjust the position of antennas dynamically, which adjusts the steering vector in real-time, thereby adapting to the varying environments throughout flight. Bai *et al.* proposed a soft A2C algorithm, which designs the trajectory of UAV and the direction of antennas' main lobe based on the elevation and azimuth angles of ground devices. It effectively improves the channel condition and reduces the time required for UAV to collect data [132]. However, uploading the collected data directly may cause the leakage of sensitive information. FL adopts a decentralized framework, enabling users to upload model parameters rather than local data to protect privacy. Thus, the application of FL in air-ground network with FLA can achieve multiple enhancements in data security, transmission delay and coverage area. Zhao *et al.* proposed a PDD approach to jointly optimize the position of antennas, beamforming, and user selection strategy, thereby accelerating the convergence of FL [133]. To deal with the dynamic environments, Ahmadzadeh *et al.* adopted a recurrent deterministic policy gradient algorithm to extract the potential features of state variations through constant interaction with the environment [134]. Furthermore, the position of antennas can be adjusted adaptively to minimize the gap between the global model and the optimal model.

D. Communication and Sensing Network

1) Vehicular Communications: With the development of emerging applications such as autonomous driving, vehicular communications network faces more challenges. As shown in Fig. 13, during the vehicle driving, the signal is easily interfered by obstacles, causing variations in propagation path and delay. Severely, the vehicle may lose data, which threatens the safety of driving. For example, in the highway scenario, the average blockage duration can be several seconds. Tunc *et al.* indicated that increasing the number of BSs can effectively reduce the blockage probability and duration [135]. Gao *et al.* proposed a hybrid beamforming approach to deal with random blockage, avoiding the construction of additional infrastructure [136]. FLA covers part of the 5G frequency bands [137], and allows BS to adjust beamforming flexibly to avoid the directions with high attenuation. On the other hand, BS can adjust the phase shift of signal on each propagation path to achieve constructive superposition at the receiver, which enhances the strength of signal. Feng *et al.* deployed FLA on vehicles and introduced deep unfolding network to accelerate the iterative optimization of receiving antenna's position and transmit beamforming, thereby maximizing the rate of the network [109]. When the vehicle moves at a faster speed, it induces doppler effect, which makes stable network connection more challenging. Dai *et al.* optimized the position of antennas via the PPO algorithm to reconstruct the channel mapping, thereby overcoming the doppler effect and improving the achievable rate [113]. In addition, the predictive beamforming is also considered as a solution to address the mobility of vehicles. Zhang *et al.* adopted multiple neural networks to predict future channel based on the historical CSI, which enhances spectral efficiency in the network [138]. To further reduce computational complexity, Liu *et al.* proposed an end-to-end architecture based on LSTM [139], which can directly design the beamforming for the next time slot based on the historical CSI. It bypasses the requirement of channel prediction and complex mathematical derivations, and improves the sum rate of vehicles.

2) ISAC: As vertical applications such as smart factory and smart home evolve, wireless network needs both communication and sensing frequency bands, which leads to severe spectrum congestion. To improve spectrum efficiency, ISAC allows communication and sensing functionalities to share spectrum and hardware platforms. In addition, it can achieve dual enhancements in communication rate and sensing accuracy through collaboration between communication and sensing. Therefore, ISAC is regarded as a new paradigm for future wireless networks. He *et al.* delicately designed the BS transmit beamforming to maximize the energy efficiency under the constraints of communication rate and sensing beam gain [140]. Liu *et al.* analyzed the trade-off between sensing and communication from multiple perspectives, including information theory and the physical layer [141], and indicated that it can be changed via proper beamforming [142]. FLA can reconstruct the channel mapping, and adjust the correlation between the sensing channel and the communication channel to achieve a better trade-off. To minimize the transmit power of dual-function BS, Zou *et al.* proposed a sparse optimization algorithm to jointly optimize the beamforming and port selection [143]. Compared to FPA, FLA can achieve lower transmit power no matter what the thresholds for sensing signal-to-noise ratio (SNR) and communication SNR are, which

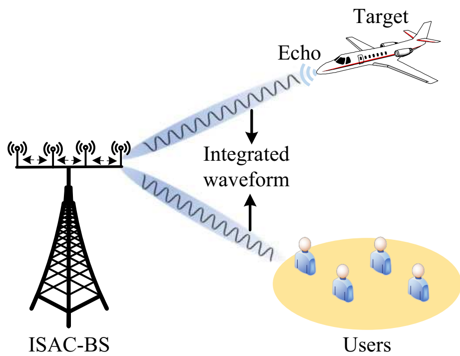


Fig. 14. The deployment of FLA in ISAC network.

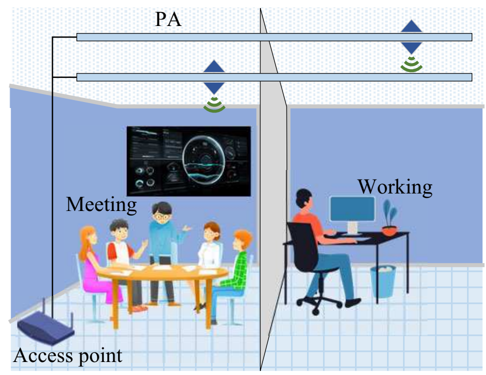


Fig. 15. The role of FLA in indoor network.

demonstrates its potential for realizing the trade-off in ISAC network. In addition, FLA provides BS with broader coverage region and enhanced interference mitigation capability, which ensures stable signal transmission. Peng *et al.* investigated full-duplex ISAC and modeled the self-interference as the function of antenna position under near-field conditions. They effectively suppressed the self-interference by jointly optimizing the beamforming and position of antennas [144]. Hung *et al.* considered ISAC secure transmission enabled by FLA, and employed PPO algorithm to maximize the secrecy rate under the constraint of sensing SINR [123]. Wang *et al.* proposed an A2C algorithm [21], which integrates pointer network and neural precoding network into the actor network to optimize the port selection and beamforming, respectively. In the sensing task, BS typically needs to sense multiple targets. However, the limited spatial resolution of FPA makes it difficult to distinguish closely spaced targets. FLA can adjust the position and orientation of antennas in real-time based on the position of targets, which introduces additional DoF and allows BS to adjust beam shape and direction more precisely. Assuming that there are multiple sensing targets in the network, Yang *et al.* first optimized the multi-beamforming by convex optimization, and then optimized the position of antennas via DDPG based on the optimized beamforming [145]. It integrates BCD algorithm with DRL and has low computational complexity, thereby achieving real-time decision-making.

E. Indoor and Outdoor Networks

1) Indoor Network: The next generation network further breaks down the barrier between physical infrastructures and the virtual world, facilitating the development of immersive communications [146]. Thus, various indoor applications are emerging, such as virtual reality and smart office, which completely changes people's lifestyle. However, the high frequency bands are allocated for these devices to achieve high-speed transmission rate, which have high propagation attenuation and weak diffraction capability, making it challenging to provide stable connection for users behind obstacles [2]. As a type of FLA, PA can overcome large-scale fading by reconstructing the LoS link. As shown in Fig. 15, the waveguides are pre-installed on the ceiling. In the right-hand office, although there is a wall blocking the propagation path between the user and the access point (AP), the LoS link can be established for the blocked user by adjusting the position of the PA on the waveguide. In the left-side office, even if there exist LoS links between the users and the AP, the propagation path can be shortened via PA to reduce attenuation. Therefore, PA is considered as a promising technology in the indoor network. Wang *et al.* studied a typical indoor network assisted by PA, and derived the successful transmission probability under the assumption that each PA is aligned with its served user [147]. Ding *et al.* modeled the ultra-dense indoor network channel by LoS blockage model and analyzed the impact of blockage on indoor network [15]. Compared to FPA, PAs can utilize blockage to suppress interference between users, thereby improving ergodic rate. Hou *et al.* studied various scenarios of PA-assisted indoor network, including single-user single-PA, single-user multi-PA and multi-user single-PA, and derived the ergodic rate with the optimal antenna position for each scenario [148]. For scenario with multi-user multi-PA, it is difficult to optimize the position of PAs to reduce path loss while avoiding interference between users. Based on the advanced feature extraction capability, AI can autonomously analyze the relationship between the distribution of users and the position of PAs, thereby adjusting PAs' position to achieve the trade-off between coverage and interference.

2) Outdoor Network: In the outdoor network, the signal transmitted from BS to users typically propagate through multipath, resulting in Rayleigh fading. On the other hand, it has become a trend to deploy more BSs in the outdoor network to provide wider coverage region. Thus, the users may suffer interference from multiple BSs, how to mitigate interference between users has become a key problem to improve quality of service [149]. The existing approaches employ BS beamforming to concentrate the power in the direction of the served users, thereby avoiding interference with unserved users while increasing the signal strength for the served users. As shown in Fig. 16, MA and FA can adjust the position of antennas over several wavelength scale, which enables more flexible beamforming. In addition, MA and FA can reconstruct the CSI, allowing the users to receive the desired signal constructively superimposed from multipath propagation, and making the interference from other BSs fall into the deep fading point. Therefore, MA and FA can enhance the capacity of outdoor network significantly. Han

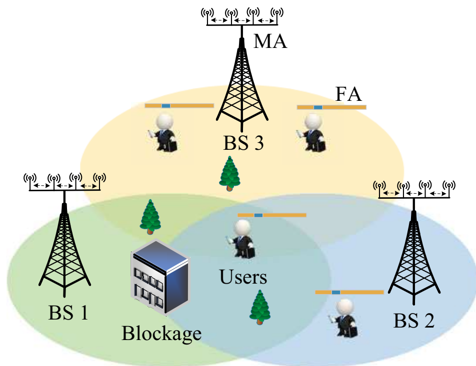


Fig. 16. The adoption of FLA in outdoor network.

et al. studied the user-centric cell-free network, where BSs employ maximum ratio transmission precoding to serve users equipped with FA [150]. By optimizing the port selection strategy, it is possible to combat fading and interference between users, which reduces the outage probability. Wei *et al.* considered MA-assisted cell-free network where both APs and users are equipped with MA [151]. To alleviate interference between users and improve energy efficiency, they proposed a dynamic neighborhood pruning PSO algorithm to jointly optimize the position of antennas and transmit beamforming. However, it requires multiple iterations for solution, leading to high computational complexity. Li *et al.* adopted a DRL-based approach to interact with the environment [152]. Specifically, they considered each AP as an agent, and obtained the antennas' position via TD3. Then, the team minimum MSE algorithm is adopted to derive digital precoding based on partial CSI, thereby reducing computation and communication overhead.

F. Lessons Learned

In this section, we summarize the application of FLA in various networks. It has been observed that most existing work focuses on designing beamforming and the position of antennas via conventional optimization methods. However, such algorithms enhance performance at the cost of high computational complexity, making it difficult to achieve the balance between performance and computation overhead. Thanks to DL's superior capability of feature extraction, it can learn the distribution of users of multiple access network. And the position of antennas and beamforming can be obtained with a single forward calculation, which reduces the computational complexity. On the other hand, RL can dynamically adjust the parameters of antennas via the interaction with the environment, allowing it to adapt to dynamic environments, such as vehicular network. In addition, FL significantly enhance the privacy of local data, especially in the air-ground network. In the future, it is expected that LLM will be able to extract deeper field knowledge, which further enhances the performance of network assisted by FLA.

V. Challenges and Future Directions

Based on the above discussion, optimizing the network enabled by FLA via AI is a promising approach. However, there are still several challenges to be addressed.

A. Standardization Issues

Establishing standards is an essential stage in the the development of FLA systems. Different types of antennas have different movement mechanisms, control protocols and movement management strategies. For example, 3DMA can adjust continuously by the stepper motor, while pixel array can only select ports at the predefined discrete position. If the user equipped with pixel array receives the continuous movement instruction from BS, it is possible to select the wrong port, leading to the deterioration of network performance. On the other hand, when multiple types of antennas coexist in the same network, the lack of coordination in the adjustment frequency of antenna parameters may exacerbate interference between users. More importantly, the radiated power of the antenna must strictly comply with national standards to prevent harmful effects on the environment, human health, and other communication systems. Therefore, it is necessary to establish uniform standards for coordinating various movement modes and standardize multiple key parameters, such as the timing of antenna adjustment and the minimum time unit. Meanwhile, the electromagnetic parameters of FLA should also be discussed, including maximum transmission power and side lobe level limitations.

B. Theoretical Foundation

Accurate theoretical modeling is the foundation for unlocking the potential of FLA in various networks. Currently, channel modeling can be divided into spatial correlation channel model and field response channel model. The aforementioned channel models only consider the spatial domain and lack consideration of the frequency domain. In addition, FLA adjusts antenna parameters in real time as the environment changes. Therefore, the channel modeling should also consider the time domain, as well as the effects of atmospheric conditions, weather variations, and other environmental factors on the channel over time. Furthermore, the network design schemes typically assume that the hardware structure is ideal. However, in the real-world scenarios, hardware impairments such as phase noises are inevitable. During the process of adjusting the antenna position, it is difficult to deployed the antenna at the desired position perfectly. Even minor control errors may have a significant impact on the performance of networks. Therefore, channel modeling needs to consider more factors, and the network design should also take into account the practical constraints caused by non-ideal hardware structure. The theoretical foundation of FLA remains to be further investigated.

C. Hardware Implementation

Although some studies have discussed the hardware implementation of FLA and designed the prototypes for wireless communications, they have not demonstrated the full potential described in the theoretical research, and the test scenarios are relatively limited. In addition, various hardware implementations of FLA are still in their infancy and face many challenges. Mechanical implementation is large in size and prone to mechanical wear during adjustment, which makes durability and miniaturization a problem. Liquid-based implementation has extremely strict requirements for antenna material, including cost, stability and electromagnetic characteristics. Reconfigurable pixel array integrates massive pixel antennas in a small scale, leading to extremely high cost. PA constructs the LoS link by adjusting the position of pinching elements manually, which makes it difficult to reconstruct channel mapping in real-time based on the environmental variations. Note that each hardware implementation has its own unique advantages and can complement each other. Combining these implementations is expected to overcome the aforementioned disadvantages and fully exploit their theoretical potential, including cost-effectiveness, response accuracy and response speed.

D. AI for Networking

AI has significantly reduced the design complexity of FLA for networking. However, a well-trained AI model requires a large amount of high-quality data. Since the current hardware implementation is still in its infancy, it is difficult to collect sufficient training samples. Thus, the academia typically utilizes simulation to establish datasets. This approach may lead to AI model learning the incorrect features due to the differences between simulation and the real world. Second, the existing AI-based network design schemes are tailored to a specific single implementation of FLA. In this case, whether these trained AI models can be transferred to other implementation types of FLA to reduce training costs is not yet well studied. Consequently, the establishment of high-quality dataset which contains multiple-dimensional features of FLA needs to be further explored. On the other hand, combining conventional approaches with AI is a promising way to enhance the generalization capability of AI model, which accommodates diverse FLA design scenarios and reduces the complexity of AI model, and making it possible to be deployed on computation-limited devices.

E. Integration with Other Technologies

1) Reconfigurable Intelligent Surface (RIS): Unlike FLA, RIS reconstructs CSI by adjusting the phase shifts of its reflecting elements. However, RIS does not exploit the characteristics of multipath and is instead adversely affected by it. On the other hand, the reconstructed link is cascaded channel, which introduces double attenuation and causes significant decrease in the received signal power. MA and FA can take advantage of multipath propagation to achieve constructive or destructive signal superposition, while PA establishes LoS link without cascaded channel, thereby avoiding severe fading. Therefore, applying FLA to RIS-assisted network can effectively address the aforementioned problems. Further, RIS provides additional controllable propagation paths for FLA systems. However, the position of antennas is deeply coupled with RIS reflection coefficients, making joint optimization extremely challenging. How to design algorithms to jointly optimize parameters to achieve their complementarity remains to be explored.

2) Simultaneous Wireless Information and Power Transfer (SWIPT): SWIPT provides an economical solution for supplying energy to massive low-power devices. However, there exists the conflict between the goals of energy harvesting and information transmission, resulting in the challenging trade-off of SWIPT. Specifically, the strong link is beneficial for energy harvesting but may introduce undue interference, which greatly reduces the SINR of information transmission. FLA has brought additional DoF to SWIPT, by adjusting the position of the receive antennas, it is possible to achieve better trade-off between information transmission and energy harvesting. Furthermore, benefiting from the capability of FLA to exploit multipath propagation environments, it is possible to improve both the performance of data transmission and energy harvesting. However, the adjustment of antenna position introduces additional power consumption, thus further investigation is needed to improve the energy efficiency of SWIPT assisted by FLA.

3) Index Modulation: As a new communication technology, index modulation does not rely on the modulation of signal amplitude, phase or frequency to carry all information. Instead, it transmits additional information by selecting different index points within the signal space. The index points can be embedded in multiple dimensions, such as antenna unit, time slot, signal constellation, or spatiotemporal matrix, thereby transmitting additional information within limited spectrum resource and power constraint. FLA has multiple adjustable parameters, including position, frequency and polarization, which can be utilized as the index points. Compared to FPA-based index modulation, the flexibility of FLA extends the index dimension, allowing BS to transmit more information with fewer antenna units, which reduces the hardware costs and improves spectrum efficiency.

F. Lessons Learned

In this section, we have discussed the challenges of intelligent FLA systems for networking. Currently, FLA is still in the early research stage, lacking the standardization of antenna parameters and movement mechanism. Furthermore, the hardware implementation remains at the prototype stage, which is difficult to be applied on a large scale, and the related theoretical foundation for channel modeling is still not well developed. The adoption of AI-enabled FLA system for networking lacks high-quality dataset. Future research should focus on the implementation approach of FLA, and explore related fundamental theories and AI design methodologies based on it. On the other hand, the integration of FLA and other technologies such as RIS, SWIPT and index modulation offers promising opportunities to further enhance spectrum efficiency.

VI. Conclusion

FLA provides additional DoF for networking, which enables comprehensive enhancement in the performance of networks. Benefiting from the powerful feature extraction capability of AI, intelligent FLA is expected to reconstruct the channel mapping in dynamic environments with low complexity. This paper provides a comprehensive survey of intelligent FLA for networking. We first reviewed the implementation approaches of FLA and some AI methods. To exploit the potential of FLA, we elaborate the role of AI in FLA design, including channel estimation, antenna position optimization, beamforming design, and parameters design for dynamic environments. Subsequently, we detailed the applications of intelligent FLA in various types of networks. Finally, we discussed the challenges and potential research directions of intelligent FLA.

References

[1] S. Chen, Y.-C. Liang, S. Sun, S. Kang, W. Cheng, and M. Peng, "Vision, requirements, and technology trend of 6G: How to tackle the challenges of system coverage, capacity, user data-rate and movement speed," *IEEE Wireless Commun.*, vol. 27, no. 2, pp. 218–228, Apr. 2020.

[2] K. Doppler, D. Lopez-Perez, S. Muniraju, T. Abrudan, S. Kucera, H. Claussen, H. Huang, H. Gacanin, V.-M. Kolmonen, and E. Rantala, "Future indoor network with a sixth sense: Requirements, challenges and enabling technologies," *Pervasive Mob. Comput.*, vol. 83, p. 101571, Jul. 2022.

[3] Z. Wang, J. Zhang, H. Du, D. Niyato, S. Cui, B. Ai, M. Debbah, K. B. Letaief, and H. V. Poor, "A tutorial on extremely large-scale MIMO for 6G: Fundamentals, signal processing, and applications," *IEEE Commun. Surv. Tutorials*, vol. 26, no. 3, pp. 1560–1605, 3rd quarter, 2024.

[4] E. Bjrnson, F. Kara, N. Kolomvakis, A. Kosasih, P. Ramezani, and M. B. Salman, "Enabling 6G performance in the upper mid-band by transitioning from massive to gigantic MIMO," *IEEE Open J. Commun. Soc.*, vol. 6, pp. 5450–5463, Jun. 2025.

[5] L. Zhu, W. Ma, W. Mei, Y. Zeng, Q. Wu, B. Ning, Z. Xiao, X. Shao, J. Zhang, and R. Zhang, "A tutorial on movable antennas for wireless networks," *IEEE Commun. Surv. Tutorials*, to appear.

[6] J. Zheng, J. Zhang, H. Du, D. Niyato, S. Sun, B. Ai, and K. B. Letaief, "Flexible-position MIMO for wireless communications: Fundamentals, challenges, and future directions," *IEEE Wireless Commun.*, vol. 31, no. 5, pp. 18–26, Oct. 2024.

[7] W. K. New, K.-K. Wong, H. Xu, C. Wang, F. R. Ghadi, J. Zhang, J. Rao, R. Murch, P. Ramrez-Espinosa, D. Morales-Jimenez, C.-B. Chae, and K.-F. Tong, "A tutorial on fluid antenna system for 6G networks: Encompassing communication theory, optimization methods and hardware designs," *IEEE Commun. Surv. Tutorials*, vol. 27, no. 4, pp. 2325–2377, Aug. 2025.

[8] Y. Ye, L. You, J. Wang, H. Xu, K.-K. Wong, and X. Gao, "Fluid antenna-assisted MIMO transmission exploiting statistical CSI," *IEEE Commun. Lett.*, vol. 28, no. 1, pp. 223–227, Jan. 2024.

[9] L. Zhu, W. Ma, and R. Zhang, "Movable-antenna array enhanced beamforming: Achieving full array gain with null steering," *IEEE Commun. Lett.*, vol. 27, no. 12, pp. 3340–3344, Dec. 2023.

[10] W. Ma, L. Zhu, and R. Zhang, "Multi-beam forming with movable-antenna array," *IEEE Commun. Lett.*, vol. 28, no. 3, pp. 697–701, Mar. 2024.

[11] Y. Jay Guo, C. A. Guo, M. Li, and M. Latva-aho, "Antenna technologies for 6G-advances and challenges," *IEEE Trans. Antennas Propag.*, to appear.

[12] L. Zhu, W. Ma, and R. Zhang, "Modeling and performance analysis for movable antenna enabled wireless communications," *IEEE Trans. Wireless Commun.*, vol. 23, no. 6, pp. 6234–6250, Jun. 2024.

[13] K.-K. Wong and K.-F. Tong, "Fluid antenna multiple access," *IEEE Trans. Wireless Commun.*, vol. 21, no. 7, pp. 4801–4815, Jul. 2022.

[14] Z. Ding, R. Schober, and H. Vincent Poor, "Flexible-antenna systems: A pinching-antenna perspective," *IEEE Trans. Commun.*, to appear.

[15] Z. Ding and H. V. Poor, "LoS blockage in pinching-antenna systems: Curse or blessing?," *IEEE Wireless Commun. Lett.*, vol. 14, no. 9, pp. 2798–2802, Sept. 2025.

[16] G. Hu, Q. Wu, K. Xu, J. Ouyang, J. Si, Y. Cai, and N. Al-Dhahir, "Fluid antennas-enabled multiuser uplink: A low-complexity gradient descent for total transmit power minimization," *IEEE Commun. Lett.*, vol. 28, no. 3, pp. 602–606, Mar. 2024.

[17] L. Zhu, X. Pi, W. Ma, Z. Xiao, and R. Zhang, "Dynamic beam coverage for satellite communications aided by movable-antenna array," *IEEE Trans. Wireless Commun.*, vol. 24, no. 3, pp. 1916–1933, Mar. 2025.

[18] Y. Zhou, W. Chen, Q. Wu, X. Zhu, and N. Cheng, "Movable antenna empowered downlink NOMA systems: Power allocation and antenna position optimization," *IEEE Wireless Commun. Lett.*, vol. 13, no. 10, pp. 2772–2776, Oct. 2024.

[19] Z. Xiao, X. Pi, L. Zhu, X.-G. Xia, and R. Zhang, "Multiuser communications with movable-antenna base station: Joint antenna positioning, receive combining, and power control," *IEEE Trans. Wireless Commun.*, vol. 23, no. 12, pp. 19744–19759, Dec. 2024.

[20] J.-M. Kang, "Deep learning enabled multicast beamforming with movable antenna array," *IEEE Wireless Commun. Lett.*, vol. 13, no. 7, pp. 1848–1852, Jul. 2024.

[21] C. Wang, G. Li, H. Zhang, K.-K. Wong, Z. Li, D. W. K. Ng, and C.-B. Chae, "Fluid antenna system liberating multiuser MIMO for ISAC via deep reinforcement learning," *IEEE Trans. Wireless Commun.*, vol. 23, no. 9, pp. 10879–10894, Sept. 2024.

[22] M. Ahmadzadeh, S. Pakravan, and G. A. Hodtani, "Movable antenna design for UAV-aided federated learning via deep reinforcement learning," in *Proc. IKT*, pp. 91–95, Isfahan, Iran, Islamic Republic of, Dec. 2024.

[23] E. Tang, W. Guo, H. He, S. Song, J. Zhang, and K. B. Letaief, "Accurate and fast channel estimation for fluid antenna systems with diffusion models," *arXiv preprint arXiv:2505.04930*, 2025.

[24] C. He, Y. Lu, B. Ai, O. A. Dobre, Z. Ding, and D. Niyato, "ICGNN: Graph neural network enabled scalable beamforming for MISO interference channels," *IEEE Trans. Mob. Comput.*, vol. 24, no. 10, pp. 10778–10791, Oct. 2025.

[25] J. Zhao, H. Quan, M. Xia, and D. Wang, "Adaptive resource allocation for mobile edge computing in internet of vehicles: A deep reinforcement learning approach," *IEEE Trans. Veh. Technol.*, vol. 73, no. 4, pp. 5834–5848, Apr. 2024.

[26] Q. Mao, F. Hu, and Q. Hao, "Deep learning for intelligent wireless networks: A comprehensive survey," *IEEE Commun. Surv. Tutorials*, vol. 20, no. 4, pp. 2595–2621, 4th quarter, 2018.

[27] Z. Wang, J. Du, X. Hou, J. Wang, C. Jiang, X.-P. Zhang, and Y. Ren, "Toward communication optimization for future underwater networking: A survey of reinforcement learning-based approaches," *IEEE Commun. Surv. Tutorials*, vol. 27, no. 5, pp. 2765–2793, Oct. 2025.

[28] O. A. Wahab, A. Mourad, H. Otrok, and T. Taleb, "Federated machine learning: Survey, multi-level classification, desirable criteria and future directions in communication and networking systems," *IEEE Commun. Surv. Tutorials*, vol. 23, no. 2, pp. 1342–1397, 2nd quarter, 2021.

[29] H. Li, M. Xiao, K. Wang, R. Schober, D. I. Kim, and Y. L. Guan, "Joint user association and beamforming design for ISAC networks with large language models," *IEEE Open J. Commun. Soc.*, vol. 6, pp. 7620–7644, Sept. 2025.

[30] M. R. Castellanos, S. Yang, C.-B. Chae, and R. W. Heath, "Embracing reconfigurable antennas in the tri-hybrid MIMO architecture for 6G and beyond," *IEEE Trans. Commun.*, to appear.

[31] W.-J. Lu, C.-X. He, Y. Zhu, K.-F. Tong, K.-K. Wong, H. Shin, and T. J. Cui, "Fluid antennas: Reshaping intrinsic properties for flexible radiation characteristics in intelligent wireless networks," *IEEE Commun. Mag.*, vol. 63, no. 5, pp. 40–45, May 2025.

[32] H. Hong, K.-K. Wong, C.-B. Chae, H. Xu, X. Guo, F. R. Ghadi, Y. Chen, Y. Xu, B. Liu, K.-F. Tong, and Y. Zhang, "A contemporary survey on fluid antenna systems: Fundamentals and networking perspectives," *IEEE Trans. Network Sci. Eng.*, to appear.

[33] L. Zhu, W. Ma, and R. Zhang, "Movable antennas for wireless communication: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 62, no. 6, pp. 114–120, Jun. 2024.

[34] X. Shao and R. Zhang, "6DMA enhanced wireless network with flexible antenna position and rotation: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 63, no. 4, pp. 121–128, Apr. 2025.

[35] X. Shao, W. Mei, C. You, Q. Wu, B. Zheng, C.-X. Wang, J. Li, R. Zhang, R. Schober, L. Zhu, W. Zhuang, and X. Shen, "A tutorial on six-dimensional movable antenna for 6G networks: Synergizing positionable and rotatable antennas," *IEEE Commun. Surv. Tutorials*, to appear.

[36] Z. Yang, N. Wang, Y. Sun, Z. Ding, R. Schober, G. K. Karagiannidis, V. W. Wong, and O. A. Dobre, "Pinching antennas: Principles, applications and challenges," *arXiv preprint arXiv:2501.10753*, 2025.

[37] Y. Liu, Z. Wang, X. Mu, C. Ouyang, X. Xu, and Z. Ding, "Pinching-antenna systems: Architecture designs, opportunities, and outlook," *IEEE Commun. Mag.*, to appear.

[38] M. Zeng, J. Wang, O. A. Dobre, Z. Ding, G. K. Karagiannidis, R. Schober, and H. V. Poor, "Resource allocation for pinching-

antenna systems: State-of-the-art, key techniques and open issues," *arXiv preprint arXiv:2506.06156*, 2025.

[39] Y. Huang, L. Xing, C. Song, S. Wang, and F. Elhouni, "Liquid antennas: Past, present and future," *IEEE Open J. Antennas Propag.*, vol. 2, pp. 473–487, Mar. 2021.

[40] K.-F. Tong, B. Liu, and K.-K. Wong, "Designs and challenges in fluid antenna system hardware," *Electronics*, vol. 14, no. 7, Apr. 2025.

[41] T. Wu, K. Zhi, J. Yao, X. Lai, J. Zheng, H. Niu, M. Elkashlan, K.-K. Wong, C.-B. Chae, Z. Ding, *et al.*, "Fluid antenna systems enabling 6G: Principles, applications, and research directions," *arXiv preprint arXiv:2412.03839*, 2024.

[42] B. Ning, S. Yang, Y. Wu, P. Wang, W. Mei, C. Yuen, and E. Bjornson, "Movable antenna-enhanced wireless communications: General architectures and implementation methods," *IEEE Wireless Commun.*, vol. 32, no. 5, pp. 108–116, Oct. 2025.

[43] Z. Li, J. Ba, Z. Su, J. Huang, H. Peng, W. Chen, L. Du, and T. H. Luan, "Movable antennas enabled ISAC systems: Fundamentals, opportunities, and future directions," *IEEE Wireless Commun.*, to appear.

[44] B. Zheng, T. Ma, C. You, J. Tang, R. Schober, and R. Zhang, "Rotatable antenna enabled wireless communication and sensing: Opportunities and challenges," *arXiv preprint arXiv:2505.16828*, 2025.

[45] X. Xiong, B. Zheng, W. Wu, W. Zhu, M. Wen, S. Lin, and Y. Zeng, "Intelligent rotatable antenna for integrated sensing, communication, and computation: Challenges and opportunities," *arXiv preprint arXiv:2506.13586*, 2025.

[46] W. Liu, X. Zhang, C. Wang, J. Ren, and W. Yuan, "Movable antennas meet low-altitude wireless networks: Fundamentals, opportunities, and future directions," *arXiv preprint arXiv:2506.13250*, 2025.

[47] C. Wang, Z. Li, K.-K. Wong, R. Murch, C.-B. Chae, and S. Jin, "AI-empowered fluid antenna systems: Opportunities, challenges, and future directions," *IEEE Wireless Commun.*, vol. 31, no. 5, pp. 34–41, Oct. 2024.

[48] C. Wang, K.-K. Wong, Z. Li, L. Jin, and C.-B. Chae, "Large language model empowered design of fluid antenna systems: Challenges, frameworks, and case studies for 6G," *arXiv preprint arXiv:2506.14288*, 2025.

[49] A. Boukarkar, X. Q. Lin, Y. Jiang, and X. F. Yang, "A compact frequency-reconfigurable 36-states patch antenna for wireless applications," *IEEE Antennas Wirel. Propag. Lett.*, vol. 17, no. 7, pp. 1349–1353, Jul. 2018.

[50] Z. Dong, Z. Zhou, Z. Xiao, C. Zhang, X. Li, H. Min, Y. Zeng, S. Jin, and R. Zhang, "Movable antenna for wireless communications: Prototyping and experimental results," *arXiv preprint arXiv:2408.08588*, 2024.

[51] Y. Shen, B. Tang, S. Gao, K.-F. Tong, H. Wong, K.-K. Wong, and Y. Zhang, "Design and implementation of mmwave surface wave enabled fluid antennas and experimental results for fluid antenna multiple access," *arXiv preprint arXiv:2405.09663*, 2024.

[52] J. Zhang, J. Rao, Z. Li, Z. Ming, C.-Y. Chiu, K.-K. Wong, K.-F. Tong, and R. Murch, "A novel pixel-based reconfigurable antenna applied in fluid antenna systems with high switching speed," *IEEE Open J. Antennas Propag.*, vol. 6, no. 1, pp. 212–228, Feb. 2025.

[53] H. O. Y. Suzuki and K. Kawai, "Pinching antenna: Using a dielectric waveguide as an antenna," *NTT DOCOMO Technical J*, vol. 23, no. 3, pp. 5–12, Jan. 2022.

[54] E. Bruce and A. Beck, "Experiments with directivity steering for fading reduction," *Proc. Inst. Radio Eng.*, vol. 23, no. 4, pp. 357–371, Apr. 1935.

[55] R. L. Haupt and M. Lanagan, "Reconfigurable antennas," *IEEE Antennas Propag. Mag.*, vol. 55, no. 1, pp. 49–61, Mar. 2013.

[56] C. J. You, S. H. Liu, J. X. Zhang, X. Wang, Q. Y. Li, G. Q. Yin, and Z. G. Wang, "Frequency- and pattern-reconfigurable antenna array with broadband tuning and wide scanning angles," *IEEE Trans. Antennas Propag.*, vol. 71, no. 6, pp. 5398–5403, Jun. 2023.

[57] J. Lu, H. C. Zhang, P. H. He, M. Wang, and T. J. Cui, "Pattern reconfigurable yagi antenna based on active corrugated stripline," *IEEE Trans. Antennas Propag.*, vol. 71, no. 1, pp. 1011–1016, Jan. 2023.

[58] H. Wang, A. Li, Y.-F. Liu, Q. Qin, L. Song, and Y. Li, "Achievable rate maximization pattern design for reconfigurable MIMO antenna array," *IEEE Trans. Wireless Commun.*, vol. 22, no. 9, pp. 5884–5897, Sept. 2023.

[59] M. Chen, S. Lei, J. Shu, K. Sun, B. Chen, and H. Hu, "High-gain, low-cost polarization-reconfigurable antenna with switchable single and dual beams by digital phase-coding method," *IEEE Trans. Antennas Propag.*, vol. 73, no. 6, pp. 3639–3653, Jun. 2025.

[60] K. Ramahatla, M. Mosalaosi, A. Yahya, and B. Basutli, "Multiband reconfigurable antennas for 5G wireless and cubesat applications: A review," *IEEE Access*, vol. 10, pp. 40910–40931, Apr. 2022.

[61] V. Suryapaga and V. V. Khairnar, "Review on multifunctional pattern and polarization reconfigurable antennas," *IEEE Access*, vol. 12, pp. 90218–90251, Jun. 2024.

[62] S. Dubal and A. Chaudhari, "Mechanisms of reconfigurable antenna: A review," in *2020 10th International Conference on Cloud Computing, Data Science and Engineering*, pp. 576–580, Noida, India, Jan. 2020.

[63] D. Comite, P. Burghignoli, P. Baccarelli, and A. Galli, "2-D beam scanning with cylindrical-leaky-wave-enhanced phased arrays," *IEEE Trans. Antennas Propag.*, vol. 67, no. 6, pp. 3797–3808, Jun. 2019.

[64] H. Pablo Zapata Cano, Z. D. Zaharis, T. V. Yioultsis, N. V. Kantartzis, and P. I. Lazaridis, "Pattern reconfigurable antennas at millimeter-wave frequencies: A comprehensive survey," *IEEE Access*, vol. 10, pp. 83029–83042, Aug. 2022.

[65] Y. Peng, S.-L. Chen, W. Zhang, X. Ruan, H. Liu, and Y. Liu, "Realization of low-profile and reconfigurable multilinear polarization states for cavity-backed magneto-electric-dipole antenna," *IEEE Antennas Wirel. Propag. Lett.*, vol. 23, no. 10, pp. 2840–2844, Oct. 2024.

[66] Z. Chen, W. Hu, C. Lin, C. Li, L. Wen, W. Jiang, and S. Gao, "Wideband horizontally omnidirectional, polarization-reconfigurable, cylindrical antenna based on combined common and differential modes," *IEEE Trans. Antennas Propag.*, vol. 73, no. 1, pp. 600–605, Jan. 2025.

[67] R. S. Baker, "Marconi's achievement," *McClure's Mag.*, vol. 18, pp. 4–12, Feb. 1902.

[68] X. Shao, Q. Jiang, and R. Zhang, "6D movable antenna based on user distribution: Modeling and optimization," *IEEE Trans. Wireless Commun.*, vol. 24, no. 1, pp. 355–370, Jan. 2025.

[69] H. Fayad and P. Record, "Mechanically steerable dielectric fluid antenna," *AEU Int. J. Electron. Commun.*, vol. 63, no. 6, pp. 506–512, Jun. 2009.

[70] K.-K. Wong, K.-F. Tong, Y. Zhang, and Z. Zhongbin, "Fluid antenna system for 6G: When bruce lee inspires wireless communications," *Electron. Lett.*, vol. 56, no. 24, pp. 1288–1290, Nov. 2020.

[71] Z. Wang, C. Ouyang, X. Mu, Y. Liu, and Z. Ding, "Modeling and beamforming optimization for pinching-antenna systems," *IEEE Trans. Commun.*, to appear.

[72] X. Xu, X. Mu, Y. Liu, and A. Nallanathan, "Joint transmit and pinching beamforming for PASS: Optimization-based or learning-based?," *arXiv preprint arXiv:2502.08637*, 2025.

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

[74] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Commun. ACM*, vol. 60, no. 6, pp. 84–90, May 2017.

[75] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997.

[76] J. Zhang, W. Lu, C. Xing, N. Zhao, N. Al-Dhahir, G. K. Karagiannidis, and X. Yang, "Intelligent integrated sensing and communication: a survey," *Sci. China Inf. Sci.*, vol. 68, no. 3, art no. 131301:1-42, Mar. 2025.

[77] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is all you need," in *Proc. NIPS*, pp. 6000–6010, California, USA, Dec. 2017.

[78] K. Arulkumaran, M. P. Deisenroth, M. Brundage, and A. A. Bharath, "Deep reinforcement learning: A brief survey," *IEEE Signal Process Mag.*, vol. 34, no. 6, pp. 26–38, Nov. 2017.

[79] B. Kiumarsi, K. G. Vamvoudakis, H. Modares, and F. L. Lewis, "Optimal and autonomous control using reinforcement learning: A survey," *IEEE Trans. Neural Networks Learn. Syst.*, vol. 29, no. 6, pp. 2042–2062, Jun. 2018.

[80] N. C. Luong, D. T. Hoang, S. Gong, D. Niyato, P. Wang, Y.-C. Liang, and D. I. Kim, "Applications of deep reinforcement learning in communications and networking: A survey," *IEEE Commun. Surv. Tutorials*, vol. 21, no. 4, pp. 3133–3174, 4th quarter, 2019.

[81] W. Y. B. Lim, N. C. Luong, D. T. Hoang, Y. Jiao, Y.-C. Liang, Q. Yang, D. Niyato, and C. Miao, "Federated learning in mobile edge networks: A comprehensive survey," *IEEE Commun. Surv. Tutorials*, vol. 22, no. 3, pp. 2031–2063, 3rd quarter, 2020.

[82] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Proc. AISTATS*, pp. 1273–1282, Florida, USA, 2017.

[83] Q. Duan, J. Huang, S. Hu, R. Deng, Z. Lu, and S. Yu, "Combining federated learning and edge computing toward ubiquitous intelligence in 6G network: Challenges, recent advances, and future directions,"

IEEE Commun. Surv. Tutorials, vol. 25, no. 4, pp. 2892–2950, 4th quarter, 2023.

[84] W. Ma, L. Zhu, and R. Zhang, “Compressed sensing based channel estimation for movable antenna communications,” *IEEE Commun. Lett.*, vol. 27, no. 10, pp. 2747–2751, Oct. 2023.

[85] Z. Xiao, S. Cao, L. Zhu, Y. Liu, B. Ning, X.-G. Xia, and R. Zhang, “Channel estimation for movable antenna communication systems: A framework based on compressed sensing,” *IEEE Trans. Wireless Commun.*, vol. 23, no. 9, pp. 11814–11830, Sept. 2024.

[86] C. Skouroumounis and I. Krikidis, “Fluid antenna with linear MMSE channel estimation for large-scale cellular networks,” *IEEE Trans. Commun.*, vol. 71, no. 2, pp. 1112–1125, Feb. 2023.

[87] S. Ji, C. Psomas, and J. Thompson, “Correlation-based machine learning techniques for channel estimation with fluid antennas,” in *Proc. ICASSP*, pp. 8891–8895, Seoul, Republic of Korea, Mar. 2024.

[88] H. Wang, L. Wang, Z. Wang, L. Ge, G. Chen, and F. Gao, “Deep learning based channel estimation for massive MIMO: A sparsity adaptive compressive sensing method and FPGA implementation,” *IEEE Trans. Cognit. Commun. Networking*, to appear.

[89] Z. Chai, K.-K. Wong, K.-F. Tong, Y. Chen, and Y. Zhang, “Port selection for fluid antenna systems,” *IEEE Commun. Lett.*, vol. 26, no. 5, pp. 1180–1184, May 2022.

[90] H. Zhang, J. Wang, C. Wang, C.-C. Wang, K.-K. Wong, B. Wang, and C.-B. Chae, “Learning-induced channel extrapolation for fluid antenna systems using asymmetric graph masked autoencoder,” *IEEE Wireless Commun. Lett.*, vol. 13, no. 6, pp. 1665–1669, Jun. 2024.

[91] S. Jang and C. Lee, “New view of learning-aided channel estimation for movable antenna systems,” *IEEE Trans. Wireless Commun.*, vol. 24, no. 7, pp. 5694–5708, Jul. 2025.

[92] Y. Zhang, H. Yin, W. Li, E. Bjrnson, and M. Debbah, “Port-LLM: A port prediction method for fluid antenna based on large language models,” *IEEE Trans. Commun.*, to appear.

[93] H. Yang, S. Lambotharan, and M. Derakhshani, “FAS-LLM: Large language model-based channel prediction for OTFS-enabled satellite-FAS links,” *arXiv preprint arXiv:2505.09751*, 2025.

[94] C. N. Efrem and I. Krikidis, “Transmit and receive antenna port selection for channel capacity maximization in fluid-MIMO systems,” *IEEE Wireless Commun. Lett.*, vol. 13, no. 11, pp. 3202–3206, Nov. 2024.

[95] L. Zhang, H. Yang, Y. Zhao, and J. Hu, “Joint port selection and beamforming design for fluid antenna assisted integrated data and energy transfer,” *IEEE Wireless Commun. Lett.*, vol. 13, no. 7, pp. 1833–1837, Jul. 2024.

[96] T. Mao, Z. Chu, Y. Wang, Z. Zhu, W. Hao, D. Mi, and C. Pan, “Joint time scheduling and port activation design for fluid antenna-empowered wireless powered communication networks,” *IEEE Internet Things J.*, vol. 12, no. 13, pp. 22904–22914, Jul. 2025.

[97] Z. Chai, K.-K. Wong, K.-F. Tong, Y. Chen, and Y. Zhang, “Performance of machine learning aided fluid antenna system with improved spatial correlation model,” in *Proc. 6GNet*, Paris, France, Jul. 2022.

[98] M. Eskandari, A. G. Burr, K. Cumanan, and K.-K. Wong, “cGAN-based slow fluid antenna multiple access,” *IEEE Wireless Commun. Lett.*, vol. 13, no. 10, pp. 2907–2911, Oct. 2024.

[99] J. Zou, S. Sun, and C. Wang, “Online learning-induced port selection for fluid antenna in dynamic channel environment,” *IEEE Wireless Commun. Lett.*, vol. 13, no. 2, pp. 313–317, Feb. 2024.

[100] W. Ma, L. Zhu, and R. Zhang, “MIMO capacity characterization for movable antenna systems,” *IEEE Trans. Wireless Commun.*, vol. 23, no. 4, pp. 3392–3407, Apr. 2024.

[101] C. He, Y. Lu, W. Chen, B. Ai, K.-K. Wong, and D. Niyato, “Graph neural network enabled fluid antenna systems: A two-stage approach,” *IEEE Trans. Veh. Technol.*, vol. 74, no. 10, pp. 16625–16629, Oct. 2025.

[102] J. Guo, Y. Liu, and A. Nallanathan, “A graph neural network for learning beamforming in pinching antenna systems (PASS),” *IEEE Wireless Communications Letters*, to appear.

[103] S. Khisa, A. Amhaz, M. Elhattab, C. Assi, and S. Sharafeddine, “Meta-learning driven movable-antenna-assisted full-duplex RSMA for multi-user communication: Performance and optimization,” *arXiv preprint arXiv:2504.03982*, 2025.

[104] C. Weng, Y. Chen, L. Zhu, and Y. Wang, “Learning-based joint beamforming and antenna movement design for movable antenna systems,” *IEEE Wireless Commun. Lett.*, vol. 13, no. 8, pp. 2120–2124, Aug. 2024.

[105] C. Xie, Y. Xiu, S. Yang, and Z. Zhang, “Deep learning for movable antenna precoding in 2D MISO communication system,” in *Proc. ICCC*, pp. 2500–2504, Chengdu, China, Dec. 2024.

[106] X. Tang, Y. Jiang, J. Liu, Q. Du, D. Niyato, and Z. Han, “Deep learning-assisted jamming mitigation with movable antenna array,” *IEEE Trans. Veh. Technol.*, vol. 74, no. 9, pp. 14865–14870, Sept. 2025.

[107] H. Ma, W. Mei, X. Wei, B. Ning, and Z. Chen, “Robust movable-antenna position optimization with imperfect CSI for MISO systems,” *IEEE Commun. Lett.*, vol. 29, no. 7, pp. 1594–1598, Jul. 2025.

[108] X. Chen, B. Feng, Y. Wu, D. W. Kwan Ng, and R. Schober, “Joint beamforming and antenna movement design for moveable antenna systems based on statistical CSI,” in *Proc. GLOBECOM*, pp. 4387–4392, Kuala Lumpur, Malaysia, Dec. 2023.

[109] B. Feng, C. Feng, K.-K. Wong, and T. Q. S. Quek, “Deep unfolding neural networks for fluid antenna-enhanced vehicular communication,” *IEEE Trans. Veh. Technol.*, vol. 74, no. 9, pp. 14793–14798, Sept. 2025.

[110] X. Xie, Y. Lu, and Z. Ding, “Graph neural network enabled pinching antennas,” *IEEE Wireless Commun. Lett.*, vol. 14, no. 9, pp. 2982–2986, Sept. 2025.

[111] Q. Xue, Y.-J. Liu, Y. Sun, J. Wang, L. Yan, G. Feng, and S. Ma, “Beam management in ultra-dense mmwave network via federated reinforcement learning: An intelligent and secure approach,” *IEEE Trans. Cognit. Commun. Networking*, vol. 9, no. 1, pp. 185–197, Feb. 2023.

[112] T. Zhao, M. Li, and Y. Pan, “Online learning-based reconfigurable antenna mode selection exploiting channel correlation,” *IEEE Trans. Wireless Commun.*, vol. 20, no. 10, pp. 6820–6834, Oct. 2021.

[113] J. Dai, Y. Liu, J. Zheng, R. Zhang, J. Zhang, and B. Ai, “Movable cell-free massive MIMO for high-speed train communications: A PPO-based antenna position optimization,” in *Proc. ICC*, pp. 38–43, Montreal, QC, Canada, Jue. 2025.

[114] N. Waqar, K.-K. Wong, C.-B. Chae, R. Murch, S. Jin, and A. Sharples, “Opportunistic fluid antenna multiple access via team-inspired reinforcement learning,” *IEEE Trans. Wireless Commun.*, vol. 23, no. 9, pp. 12068–12083, Sept. 2024.

[115] S. M. R. Islam, N. Avazov, O. A. Dobre, and K.-s. Kwak, “Power-domain non-orthogonal multiple access (NOMA) in 5G systems: Potentials and challenges,” *IEEE Commun. Surv. Tutorials*, vol. 19, no. 2, pp. 721–742, 2nd quarter, 2017.

[116] Z. Zhou, Z. Yang, G. Chen, and Z. Ding, “Sum-rate maximization for NOMA-assisted pinching-antenna systems,” *IEEE Wireless Commun. Lett.*, vol. 14, no. 9, pp. 2728–2732, Sept. 2025.

[117] H. Han, X. Jiang, W. Lu, W. Zhai, Y. Li, N. Kumar, and M. Guizani, “A multi-agent reinforcement learning approach for massive access in NOMA-URLLC networks,” *IEEE Trans. Veh. Technol.*, vol. 72, no. 12, pp. 16799–16804, Dec. 2023.

[118] K.-K. Wong, D. Morales-Jimenez, K.-F. Tong, and C.-B. Chae, “Slow fluid antenna multiple access,” *IEEE Trans. Commun.*, vol. 71, no. 5, pp. 2831–2846, May 2023.

[119] N. Waqar, K.-K. Wong, K.-F. Tong, A. Sharples, and Y. Zhang, “Deep learning enabled slow fluid antenna multiple access,” *IEEE Commun. Lett.*, vol. 27, no. 3, pp. 861–865, Mar. 2023.

[120] D. Wang, B. Bai, W. Zhao, and Z. Han, “A survey of optimization approaches for wireless physical layer security,” *IEEE Commun. Surv. Tutorials*, vol. 21, no. 2, pp. 1878–1911, 2nd quarter, 2019.

[121] G. Hu, Q. Wu, D. Xu, K. Xu, J. Si, Y. Cai, and N. Al-Dhahir, “Movable antennas-assisted secure transmission without eavesdroppers’ instantaneous CSI,” *IEEE Trans. Mob. Comput.*, vol. 23, no. 12, pp. 14263–14279, Dec. 2024.

[122] J. Tang, C. Pan, Y. Zhang, H. Ren, and K. Wang, “Secure MIMO communication relying on movable antennas,” *IEEE Trans. Commun.*, vol. 73, no. 4, pp. 2159–2175, Apr. 2025.

[123] H. L. Hung, N. H. Huy, N. C. Luong, Q.-V. Pham, D. Niyato, and N. T. Hoa, “Beamforming design for physical security in movable antenna-aided ISAC systems: A reinforcement learning approach,” *IEEE Trans. Veh. Technol.*, to appear.

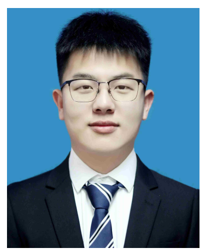
[124] X. Chen, J. An, Z. Xiong, C. Xing, N. Zhao, F. R. Yu, and A. Nallanathan, “Covert communications: A comprehensive survey,” *IEEE Commun. Surv. Tutorials*, vol. 25, no. 2, pp. 1173–1198, 2nd quarter, 2023.

[125] H. Jiang, Z. Wang, and Y. Liu, “Pinching-antenna system (PASS) enhanced covert communications,” *arXiv preprint arXiv:2504.10442*, 2025.

[126] H. Mao, X. Pi, L. Zhu, Z. Xiao, X.-G. Xia, and R. Zhang, “Sum rate maximization for movable antenna enhanced multiuser covert communications,” *IEEE Wireless Commun. Lett.*, vol. 14, no. 3, pp. 611–615, Mar. 2025.

[127] W. Xie, Z. Li, C. Yu, H. Xu, J. Wang, W. Wu, X. Li, and L. Yang, “Movable-antenna-assisted covert communications with reconfigurable

intelligent surfaces," *IEEE Internet Things J.*, vol. 12, no. 9, pp. 12369–12382, May 2025.
[128] J. Heo, S. Sung, H. Lee, I. Hwang, and D. Hong, "MIMO satellite communication systems: A survey from the PHY layer perspective," *IEEE Commun. Surv. Tutorials*, vol. 25, no. 3, pp. 1543–1570, 3rd quarter, 2023.
[129] L. Lin, J. Ding, Z. Zhou, and B. Jiao, "Power-efficient full-duplex satellite communications aided by movable antennas," *IEEE Wireless Commun. Lett.*, vol. 14, no. 3, pp. 656–660, Mar. 2025.
[130] Y. Zhang, Y. Wu, A. Liu, X. Xia, T. Pan, and X. Liu, "Deep learning-based channel prediction for LEO satellite massive MIMO communication system," *IEEE Wireless Commun. Lett.*, vol. 10, no. 8, pp. 1835–1839, Aug. 2021.
[131] M. Hua, L. Yang, C. Li, Q. Wu, and A. L. Swindlehurst, "Throughput maximization for UAV-aided backscatter communication networks," *IEEE Trans. Commun.*, vol. 68, no. 2, pp. 1254–1270, Feb. 2020.
[132] Y. Bai, B. Xie, R. Zhu, Z. Chang, and R. Jntti, "Movable antenna-equipped UAV for data collection in backscatter sensor networks: A deep reinforcement learning-based approach," in *Proc. ICC*, pp. 6560–6565, Montreal, QC, Canada, Jun. 2025.
[133] Y. Zhao, M. Xu, P. Wang, and D. Niyato, "Fluid antenna enabled over-the-air federated learning: Joint optimization of positioning, beamforming, and user selection," *arXiv preprint arXiv:2503.00011*, 2025.
[134] M. Ahmadzadeh, S. Pakravan, G. A. Hodtani, M. Zeng, J.-Y. Chouinard, and L. A. Rusch, "Enhanced over-the-air federated learning using AI-based fluid antenna system," in *Proc. WCNC*, Milan, Italy, Mar. 2025.
[135] C. Tunc, M. F. zko, F. Fund, and S. S. Panwar, "The blind side: Latency challenges in millimeter wave networks for connected vehicle applications," *IEEE Trans. Veh. Technol.*, vol. 70, no. 1, pp. 529–542, Jan. 2021.
[136] M. Gao, B. Ai, Y. Niu, W. Wu, P. Yang, F. Lyu, and X. Shen, "Efficient hybrid beamforming with anti-blockage design for high-speed railway communications," *IEEE Trans. Veh. Technol.*, vol. 69, no. 9, pp. 9643–9655, Sept. 2020.
[137] H. Wang, Y. Shen, K.-F. Tong, and K.-K. Wong, "Continuous electrowetting surface-wave fluid antenna for mobile communications," in *Proc. TENCON*, pp. 1–3, Hong Kong, China, Nov. 2022.
[138] J. Zhang, G. Zheng, Y. Zhang, I. Krikidis, and K.-K. Wong, "Deep learning based predictive beamforming design," *IEEE Trans. Veh. Technol.*, vol. 72, no. 6, pp. 8122–8127, Jun. 2023.
[139] C. Liu, W. Yuan, S. Li, X. Liu, H. Li, D. W. K. Ng, and Y. Li, "Learning-based predictive beamforming for integrated sensing and communication in vehicular networks," *IEEE J. Sel. Areas Commun.*, vol. 40, no. 8, pp. 2317–2334, Aug. 2022.
[140] Z. He, W. Xu, H. Shen, Y. Huang, and H. Xiao, "Energy efficient beamforming optimization for integrated sensing and communication," *IEEE Wireless Commun. Lett.*, vol. 11, no. 7, pp. 1374–1378, Jul. 2022.
[141] F. Liu, Y. Cui, C. Masouros, J. Xu, T. X. Han, Y. C. Eldar, and S. Buzzi, "Integrated sensing and communications: Toward dual-functional wireless networks for 6G and beyond," *IEEE J. Sel. Areas Commun.*, vol. 40, no. 6, pp. 1728–1767, Jun. 2022.
[142] F. Liu, L. Zhou, C. Masouros, A. Li, W. Luo, and A. Petropulu, "Toward dual-functional radar-communication systems: Optimal waveform design," *IEEE Trans. Signal Process.*, vol. 66, no. 16, pp. 4264–4279, Aug. 2018.
[143] J. Zou, H. Xu, C. Wang, L. Xu, S. Sun, K. Meng, C. Masouros, and K.-K. Wong, "Shifting the ISAC trade-off with fluid antenna systems," *IEEE Wireless Commun. Lett.*, vol. 13, no. 12, pp. 3479–3483, Dec. 2024.
[144] S. Peng, C. Zhang, Y. Xu, Q. Wu, L. Zhu, X. Ou, and D. He, "Joint antenna position and beamforming optimization with self-interference mitigation in movable antenna aided ISAC system," in *Proc. WCNC*, pp. 1–6, Milan, Italy, Mar. 2022.
[145] S. Yang, J. Yao, J. Tang, T. Wu, M. Elkashlan, C. Yuen, M. Debbah, H. Shin, and M. Valenti, "Towards intelligent antenna positioning: Leveraging DRL for FAS-aided ISAC systems," *IEEE Internet Things J.*, vol. 12, no. 16, pp. 34615–34618, Aug. 2025.
[146] J. Du, F. R. Yu, G. Lu, J. Wang, J. Jiang, and X. Chu, "MEC-assisted immersive VR video streaming over terahertz wireless networks: A deep reinforcement learning approach," *IEEE Internet Things J.*, vol. 7, no. 10, pp. 9517–9529, Oct. 2020.
[147] Y. Wang, Y. Liu, Y. Fu, and Z. Ding, "Pinching-antenna systems for indoor immersive communications: A 3D-modeling based performance analysis," *arXiv preprint arXiv:2506.07771*, 2025.
[148] T. Hou, Y. Liu, and A. Nallanathan, "On the performance of uplink pinching antenna systems (PASS)," *IEEE Trans. Commun.*, to appear.
[149] H. A. Ammar, R. Adve, S. Shahbazpanahi, G. Boudreau, and K. V. Srinivas, "User-centric cell-free massive MIMO networks: A survey of opportunities, challenges and solutions," *IEEE Commun. Surv. Tutorials*, vol. 24, no. 1, pp. 611–652, 1st quarter, 2022.
[150] T. Han, Y. Zhu, K.-K. Wong, G. Zheng, and H. Shin, "Cell-free fluid antenna multiple access networks," *IEEE Trans. Wireless Commun.*, vol. 24, no. 9, pp. 7237–7251, Sept. 2025.
[151] H. Wei, W. Wang, W. Ni, C. Zhang, and Y. Huang, "Movable-antenna enabled cell-free networks," *IEEE Trans. Veh. Technol.*, vol. 74, no. 10, pp. 16533–16537, Oct. 2025.
[152] Q. Li, W. Wang, Y. Li, F. Yu, C. Zhang, and Y. Huang, "Deep reinforcement learning for movable antenna-assisted cell-free networks," *IEEE Wireless Commun. Lett.*, vol. 14, no. 9, pp. 2783–2787, Sept. 2025.



Xianglin Yu received the B.S. degree from Dalian University of Technology, China, in 2023. He is currently pursuing the Ph.D. degree with the School of Information and Communication Engineering, Dalian University of Technology, China. His current research interests include intelligent reflecting surface, integrated sensing and communications and flexible position antenna. He has received IEEE ICCC 2025 Best Paper Award.

Jiacheng Wang (Member, IEEE) received the M.S and Ph.D. degrees in the School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, in 2018 and 2022, respectively. From 2021 to 2022, he was a visiting researcher with College of Computing and Data Science, at Nanyang Technological University, Singapore, where he is now the Postdoc Research Fellow. His research interests include Generative AI, Integrated Sensing and Communications, Network Optimization, and Edge Intelligence. He has published more than 40 papers including IEEE JSAC, IEEE TMC, IEEE TWC, IEEE TCCN, IEEE TVT, IEEE CMOST, IEEE WCM, IEEE Network, IEEE WCL, IEEE GLOBECOM, IEEE ICC, and IEEE WCNC. He has received IEEE ICC 2025 Best Paper Award, and he was a Guest Editor of IEEE TCCN, Wireless Communications, OJCOMS, IEEE Internet of Things Magazine, and IEEE Networking Letters.

Rose Qingyang Hu (Fellow, IEEE) received the B.S. degree from the University of Science and Technology of China, the M.S. degree from New York University, and the Ph.D. degree from the University of Kansas. Besides a decade academia experience, she has more than ten years of research and development experience with Nortel, Blackberry, and Intel, as the Technical Manager, a Senior Wireless System Architect, and a Senior Research Scientist, actively participating in industrial 4G technology development, standardization, system level simulation, and performance evaluation. She is currently a Professor with the Electrical and Computer Engineering Department and the Associate Dean for Research of the College of Engineering, Utah State University. She also directs the Communications Network Innovation Laboratory, Utah State University. Her current research interests include next-generation wireless system design, the Internet of Things, cyber physical system, mobile edge computing, V2X communications, and AI/ML in wireless networks. She is a member of the Phi Kappa Phi Honor Society. She also served as the TPC Co-Chair for the IEEE ICC 2018. She is also serving on the Editorial Board for IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, and IEEE WIRELESS COMMUNICATIONS. She is an IEEE Communications Society Distinguished Lecturer Class 2015-2018, an IEEE Vehicular Technology Society Distinguished Lecturer Class 2020-2022, and a recipient of prestigious Best Paper Award from the IEEE GLOBECOM 2012, the IEEE ICC 2015, the IEEE VTC Spring, and the IEEE ICC 2016.

Dong In Kim (Life Fellow, IEEE) received the Ph.D. degree in electrical engineering from the University of Southern California, Los Angeles, CA, USA, in 1990. He was a Tenured Professor with the School of Engineering Science, Simon Fraser University, Burnaby, BC, Canada. He is currently a Distinguished Professor with the College of Information and Communication Engineering, Sungkyunkwan University, Suwon, South Korea. He is a Fellow of the Korean Academy of Science and Technology and a Life Member of the National Academy of Engineering of Korea. He was the first recipient of the NRF of Korea Engineering Research Center (ERC) in Wireless Communications for RF Energy Harvesting from 2014 to 2021. He received several research awards, including the 2023 IEEE ComSoc Best Survey Paper Award and the 2022 IEEE Best Land Transportation Paper Award. He was selected the 2019 recipient of the IEEE ComSoc Joseph LoCicero Award for Exemplary Service to Publications. He was the General Chair of the IEEE ICC 2022, Seoul. From 2001 to 2024, he served as an Editor, an Editor at Large, and an Area Editor of Wireless Communications I for IEEE Transactions on Communications. From 2002 to 2011, he served as an Editor and a Founding Area Editor of Cross-Layer Design and Optimization for IEEE Transactions on Wireless Communications. From 2008 to 2011, he served as the Co-Editor-in-Chief for the IEEE/KICS Journal of Communications and Networks. He served as the Founding Editor-in-Chief for the IEEE Wireless Communications Letters from 2012 to 2015. He has been listed as a 2020/2022 Highly Cited Researcher by Clarivate Analytics.

Naofal Al-Dhahir (Fellow, IEEE) is Erik Jonsson Distinguished Professor and ECE Associate Head at UT-Dallas. He earned his PhD degree from Stanford University and was a principal member of technical staff at GE Research Center and AT&T Shannon Laboratory from 1994 to 2003. He is co-inventor of 43 issued patents, co-author of over 650 papers and co-recipient of 8 IEEE best paper awards. He is an IEEE Fellow, AAIA Fellow, received 2019 IEEE COMSOC SPCC technical recognition award, 2021 Qualcomm faculty award, and 2022 IEEE COMSOC RCC technical recognition award. He served as Editor-in-Chief of IEEE Transactions on Communications from Jan. 2016 to Dec. 2019. He is a Fellow of the US National Academy of Inventors, a Member of the European Academy of Sciences and Arts, and a Web of Science Clarivate Highly Cited Researcher.

Henk Wymeersch (S'01, M'05, SM'19, F'24) obtained the Ph.D. degree in Electrical Engineering/Applied Sciences in 2005 from Ghent University, Belgium. He is currently a Professor of Communication Systems with the Department of Electrical Engineering at Chalmers University of Technology, Sweden and a Distinguished Visiting Professor at Tsinghua University. Prior to joining Chalmers, he was a postdoctoral researcher from 2005 until 2009 with the Laboratory for Information and Decision Systems at the Massachusetts Institute of Technology. Prof. Wymeersch served as Associate Editor for IEEE Communication Letters, IEEE Transactions on Wireless Communications, and IEEE Transactions on Communications and is currently Senior Member of the IEEE Signal Processing Magazine Editorial Board. During 2019-2021, he was an IEEE Distinguished Lecturer with the Vehicular Technology Society. His current research interests include the convergence of communication and sensing, in a 5G and Beyond 5G context.

Nan Zhao (Senior Member, IEEE) is currently a Professor at Dalian University of Technology, China. He received the Ph.D. degree in information and communication engineering in 2011, from Harbin Institute of Technology, Harbin, China. Dr. Zhao is serving on the editorial boards of IEEE Wireless Communications and IEEE Wireless Communications Letters. He won the best paper awards in IEEE VTC 2017 Spring, ICNC 2018, WCSP 2018 and WCSP 2019. He also received the IEEE Communications Society Asia Pacific Board Outstanding Young Researcher Award in 2018.