Applications of Deep Learning and Deep Reinforcement Learning in 6G Networks

Tri-Hai Nguyen, Heejae Park, Kihyun Seol, Seonghyeon So, and Laihyuk Park
Department of Computer Science and Engineering, Seoul National University of Science and Technology, Seoul, Korea
Email: {haint93, prkhj98, seolpark, thtjdgus0828, lhpark}@seoultech.ac.kr

***Abstract*—As the demand for data-driven applications and emerging technologies such as extended reality, autonomous vehicles, and the Internet of Things (IoT) continues to grow, the development of a next-generation wireless communication system, 6G, becomes necessary. To fulfill the stringent requirements of 6G networks, new enabling technologies are necessary. Deep learning (DL) and deep reinforcement learning (DRL) are two promising technologies that have gained significant attention in recent years. In this paper, we provide an overview of the applications and advancements of DL and DRL in 6G networks. We discuss the latest research and identify areas for further exploration in this field.**

***Index Terms*—6G, deep learning, deep reinforcement learning, wireless communications.**

I. Introduction

The 6th generation of wireless networks commonly referred to as 6G, is expected to revolutionize the way we interact with wireless devices and services. While 5G networks are still being rolled out, research on 6G is already underway with the goal of delivering even faster data rates, lower latency, and more reliable connectivity [1]. 6G is expected to enable many new applications and services, e.g., extended reality, autonomous vehicles, smart cities, and more [2]–[4]. 6G networks are characterized by several essential features, including the use of higher frequency bands, such as terahertz (THz), to increase data transmission rates and capacity, as well as the integration of cutting-edge technologies including artificial intelligence/machine learning (AI/ML). Other potential features of 6G networks include ultra-low latency, improved energy efficiency, and enhanced security and privacy. It is still in its early phases of development, but it has the possibility of influencing the future of wireless communication and driving innovation in a wide range of industries.

In 6G, DL and DRL - two subfields of AI/ML - have been applied in several ways, including resource allocation, network optimization, interference management, channel prediction, and mobility management, among others [5], [6]. DL, also known as deep neural networks (DNNs), is a subset of ML motivated by the structure and operation of the human nervous system [7]. DNNs are composed of multiple interconnected layers of artificial neurons that are trained to learn from massive quantities of data. This allows DNNs to automatically extract complex patterns and relationships from data and make predictions based on these patterns. DRL, on the other hand, combines reinforcement learning (RL) with DNNs [8]. RL is an area of ML that involves decision-making agents that learn by interacting with an environment and receiving rewards or penalties based on their actions. In DRL, the decision-making agent is a DNN. These AI-based approaches have shown promising results in enhancing the efficiency of 6G networks. The integration of DL and DRL with 6G networks is a rapidly growing research area that holds great potential for the development of new and innovative communication technologies. This paper briefly explores the concepts of DL, DRL, and their applications in future 6G systems.

II. Deep Learning in 6G Networks

DL is a subfield of ML that uses neural networks with many layers to model and solve complex problems [7]. It involves training a neural network to learn hierarchical representations of data by progressively transforming it from a raw input to a higher-level abstraction. The network learns to recognize patterns and features in the data, enabling it to make predictions or classifications. DL requires large amounts of labeled training data to be effective. The network is trained with an optimization technique (e.g., gradient descent), which adjusts the weights of the network's connections to minimize the error between its predictions and the correct output.

There are various significant forms of neural networks, including fully-connected neural networks (FNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs). CNNs excel at visual tasks that require them to utilize fundamental spatial features. RNNs are effective in classifying temporal correlations of data, which makes them ideal for time series problems. RNNs are used as units in Long Short-Term Memory (LSTM) approaches to learn order dependency in sequence prediction issues. Graph Neural Networks (GNNs) are types of neural networks that model a collection of nodes (entities) and edges (relationships) in a graph structure [20], [21]. Generative Adversarial Networks (GANs) can generate new data, such as images or audio, by pitting two networks against each other in a competition [22]. One of the key advantages of DL is its capacity to automatically extract features from raw data, making it well-suited for different tasks.

A. DL-enabled Applications in 6G Networks

DL has the potential to allow a wide range of intelligent services in 6G networks by providing powerful data analysis and decision-making capabilities. Table I summarizes the applications of DL in 6G networks.

TABLE I
APPLICATIONS OF DL IN 6G NETWORKS

Work	Application	DL Algorithm	Description
[9]	Power consumption minimization	FNNs, deep transfer learning	Designing cascaded neural networks and used deep transfer learning to fine-tune their parameters to ensure various QoS requirements
[10]	Energy efficiency maximization	GCNs	Proposing a graph-based deep unfolded framework for an iterative SCA method
[11]	Channel estimation	DNN	Proposing a DNN-based paradigm for channel estimation problems in gathering CSI messages
[12]	Channel modeling	ChannelGAN	Proposing a GAN-based channel modeling and generating approach called ChannelGAN, specially built for a limited number of link-level MIMO channels
[13]	Channel estimation	Different types of DNNs	Discussing of primary concerns and potential resolutions related to DL-powered wireless channel estimation and CSI feedback
[14]	Achievable sum-rate maximization	Convolutional LSTM	Proposing a DL-based scheme for predictive beamforming to reduce the signaling overhead by avoiding explicit channel tracking or prediction
[15]	Handover decision	DNN	Proposing a DNN-based prediction approach for conditional handover, where previous blockage information is used to anticipate the optimal next base station
[16]	Handover decision	CNN, RNN-LSTM	Using only SINR to predict the dynamic blockages and control the handover proactively via CNN and RNN-LSTM models
[17]	Secrecy rate maximization	DNN	Employing DNN to allocate resources for secure transmission in a NOMA network
[18]	Network intrusion detection	CNN	Suggesting a CNN-based model for network intrusion detection with various features reduction techniques
[19]	Network intrusion detection	CNN, weight-dropped LSTM	Detecting effectively network intrusions via an integrated DL model of a CNN and a weight-dropped LSTM

1) Resource Management: One of the most notable applications of DL in 6G networks is in the optimization of resource management. DL algorithms have been utilized to optimally allocate the network resources, resulting in improved system performance and increased efficiency.

In [9], an FNN-based framework was developed to allocate bandwidth and transmit power in an energy-efficient manner while meeting the QoS demands of different services. Though the optimization approach acquired a significant number of labeled training samples, the non-stationary nature of the wireless network compromised the accuracy of the pre-trained model. To cope with the issue, the authors designed cascaded neural networks and used deep transfer learning to fine-tune their parameters to ensure various QoS needs. The aim of [10] was to enhance power allocation in wireless interference networks by introducing a novel learning structure called unfolded successive convex approximation (USCA). In contrast to the original successive convex approximation (SCA) method that relied on iterative solvers and updates, the USCA approach replaces them with learnable graph convolutional neural networks (GCNs).

2) Spectrum Management: DL algorithms have been used to model wireless channels, which is important for accurately predicting signal strength and ensuring high-quality communication in various wireless communication systems.

The effectiveness of massive multiple-input multiple-output (MIMO) networks is heavily influenced by the quality of the monitored channel state information (CSI) messages. To address this issue, a study [11] suggested a DNN-based paradigm for channel estimation in obtaining CSI messages. The simulation results demonstrated that the DNN algorithm is effective in accurately reconstructing CSI and thus in achieving high-performance channel estimation for massive MIMO. In [12], the authors present ChannelGAN, which uses DL to model and generate MIMO channels in 3rd generation partnerships project (3GPP)-defined link-level scenarios. They also demonstrate two evaluation mechanisms: power comparison and cross-validation, which confirm the consistency and effectiveness of the generated channels in supporting DL-based CSI feedback.

In [13], the authors presented DL approaches to channel estimation, focusing on the key design aspects of DL model selection, training data collection, and DNN architecture design. In [14], the authors proposed a new method called CLRNet, which uses both spatial features and temporal dependency from previously estimated vehicle angles to predict future angles. The CLRNet includes several layers such as an input layer, a CNN module, an LSTM module, a fully-connected layer, and an output layer. This approach can help with the predictive beamforming design in a vehicle network with integrated sensing and communication capabilities.

3) Mobility Management: DL can be used to enhance mobility management performance in 6G networks. It can predict user mobility patterns and handover decisions, leading to better handover performance and reduced network congestion.

The susceptibility of millimeter-wave communications to blockages causes the conditional handover to make unintended early preparations due to sudden changes in signal reception power. To overcome this issue, current research suggests increasing the number of preparations, which causes a significant signaling overhead. In [15], the authors proposed a DNN model that accurately predicts the next base station, which enhances the robustness of the conditional handover. The proposed approach utilizes the signal patterns of the base station and the received power of the reference signal to learn blockage.

In [16], the authors presented a method that utilizes CNN and LSTM to enable reliable proactive handover. In future wireless networks, this technology can be used to create intelligent base stations that optimize network resources. The main feature is the estimation of potential blockages with only wireless information, i.e., the Signal Interference-to-Noise-ratio (SINR). This allows for proactive handover without the need for multimodal data, sensory hardware, or high computational requirements, which in turn reduces the computational overhead and resources required at the base stations.

4) Security and Privacy: Non-orthogonal multiple access (NOMA) can address the requirement of 6G networks for extremely high data rates and a large number of connections. This method utilizes the successive interference cancellation (SIC) technique at the receivers to cater to various users in a single resource block. To ensure privacy in a NOMA network with the objective of secrecy rate maximization, a study proposed a conventional method to generate the training dataset, which is trained by a DNN model [17]. Once trained, the model is capable of achieving nearly optimal levels of secrecy rate performance, while considerably reducing computational time compared to the baseline method.

DL algorithms have been used to detect and prevent security risks, e.g., denial-of-service (DoS) assaults and unauthorized access [18]. In [19], researchers developed a combination of a CNN and a weight-dropped LSTM (WDLSTM) model to effectively detect network intrusions.

III. Deep Reinforcement Learning in 6G Networks

RL involves an agent learning to interact with an environment by performing actions and receiving rewards or penalties based on the outputs of those actions. The agent repeats this process until it learns an optimal solution. There are two types of learning methods: model-based and model-free. The agent in model-based RL presupposes knowledge of the dynamics of the environment, such as state transitions and reward creation. This may not always be possible in complicated contexts when the agent has a limited understanding of the surroundings. As a result, model-free techniques are deployed, in which the agent learns optimum tactics without having any prior knowledge of the system.

DRL is an extension of RL that utilizes DNNs to represent the agent's policy and value functions [8]. The use of DNNs allows for the handling of high-dimensional state and action spaces, which was previously a challenge for traditional RL methods [33]. DRL provides various benefits over standard optimization approaches in the realm of wireless communications, including real-time inference capabilities. Nevertheless, the training phase of DNNs necessitates the use of large computing resources, such as GPUs and high-performance CPU clusters. When the training is completed, the agent can perform real-time decisions, giving it an edge over traditional optimization techniques. DRL is applied to sequential decision-making, which can be in the form of a Markov Decision Process (MDP) consisting of a 5-tuple (S, A, P, R, λ). Here, S represents a finite set of states, A denotes a finite set of actions, P indicates the transition probability function, R stands for the reward function, and λ represents the discount factor. At each time step, the agent observes the current state and selects an action based on its policy. Afterward, the agent receives a reward and moves to a new state, guided by the transition probabilities. The objective of the agent is to maximize its expected cumulative reward over time. Some modern DRL algorithms include deep Q-learning (DQN) [8], double deep Q-learning (DDQN) [34], and deep deterministic policy gradient (DDPG) [35].

A. DRL-enabled Applications in 6G Networks

DRL has the potential to enable a wide range of applications in 6G networks by providing intelligent decision-making capabilities in dynamic and complex environments. The selected studies of DRL in 6G networks are summarized in Table II.

1) Resource Management: Multi-access edge computing (MEC) is a promising paradigm for 6G networks that enables low-latency and high-bandwidth applications by providing computing resources and storage at the edge. Still, resource allocation and management in MEC are challenging because of the extremely dynamic and heterogeneous nature of wireless networks. Thus, DRL can be used for the optimization of computing resource allocation in MEC systems [36].

An optimization problem was introduced to improve the utilization of MEC servers by optimizing offloading strategies and resource management [23]. The problem considers the tolerable latency of the tasks, the channel environment, the history information of the channel, and the MEC server's resources with the aim of minimizing power consumption. The authors used a DQN to train the model to predict the current CSI and attain the optimum task offloading decisions in the MEC system.

Effective use of caching resources in MEC-enabled 6G networks requires optimization of edge caching due to limitations of user equipment and MEC server capacities. However, optimizing edge caching is difficult due to the dynamic and complicated nature of content popularity, and the need to protect user privacy. The work [24] introduced a privacy-preserving distributed DDPG (P2D3PG) algorithm by extending the DDPG with federated learning to preserve users' privacy while maximizing the hit rates in MEC networks.

In addition, energy harvesting is a promising technology for providing a sustainable energy supply to 6G networks. The main idea of energy harvesting is to accumulate energy from the ambient, e.g., the sun, wind, and radio signals, to power wireless devices. The efficacy of energy harvesting can be influenced by multiple factors such as the quality and

TABLE II
APPLICATIONS OF DRL IN 6G NETWORKS

Work	Application	DRL Algorithm	Description
[23]	Task offloading	DQN	Training a model based on past CSI to perform real-time computation offloading decisions that minimize the power consumption of the MEC server
[24]	Edge caching	P2D3PG	Proposing a privacy-preserving distributed DDPG (P2D3PG) algorithm to preserve the privacy of users while maximizing the hit rates of user nodes
[25]	Energy harvesting	Wolpertinger-based DDPG	Developing DDPG with Wolpertinger training model to improve the energy charging efficiency of heterogeneous and high-density dense networks
[26]	Data collection optimization (UAV-aided network)	Dueling DQN	Designing a new IoT system that uses UAVs to collect data in the most efficient way possible by finding the shortest UAV trajectory
[27]	Task offloading (UAV-aided network)	DDPG	Proposing a high altitude platform with MEC and RSMA, which can assist the aerial users in external computation
[28]	Task offloading (UAV-aided network)	DDPG	Proposing a DDPG-based algorithm to optimize the total energy usage and delay of vehicles with a delay constraint
[29]	Intrusion detection (UAV-aided network)	DDPG	Identifying intrusion attacks in UAV-assisted networks and developing DDPG-based intrusion detection system
[30]	Sum rate maximization (IRS-aided network)	DDPG	Investigating the design beamforming matrix of the base station and phase shift of the IRS
[31]	Sum rate maximization (IRS-aided network)	DDQN	Proposing a decentralized DDQN for resource management and a centralized DDQN for IRS optimization
[32]	Sum rate maximization (UAV-IRS-aided network)	DDPG	Proposing flying IRS (UAV-mounted IRS) that reflects signals from a base station on the ground to the users in the areas with weak coverage

availability of energy sources and the energy usage of devices. An energy harvesting problem was investigated in a highly random environment [25]. To solve this, the authors proposed a Wolpertinger-based DDPG (W-DDPG) method, in which a k-nearest-neighbor algorithm discretizes the DDPG actions.

2) Unmanned Aerial Vehicles (UAV)-assisted 6G Networks: DRL can be applied to control the motion of UAVs to optimize network performance [37], [38]. For instance, DRL can be used to determine the optimal trajectory and altitude for UAVs to collect data from the network. In a recent study [26], researchers designed a novel UAV-aided IoT system that relies on the UAV shortest path while maximizing the quantity of data that can be acquired from IoT devices. A DQN-based algorithm is used to achieve the optimum flight trajectory and throughput of the coverage region. After the training process, the UAV is capable of gathering data from users at a significantly higher total sum rate while using fewer resources.

The authors of [27] investigated the use of UAVs to harvest information from terrestrial devices. Unfortunately, UAVs have energy consumption issues and low computation capabilities, so they proposed offloading some of their tasks to a high-altitude platform (HAP), which trains the DDPG model to determine optimal offloading decisions. Parameter space noise was added to the DDPG in exploration to improve the training process. Considering the maximum tolerable delay of the computational tasks, in [28], the authors addressed the computation offloading problem in a HAP-assisted vehicle network, where there is no base station available on the ground. They proposed a DDPG-based algorithm to minimize the weighted sum energy usage and latency of all vehicles.

With the increase in attention to UAV-based applications, they are at risk for security threats. Hence, in [29], the authors presented a DDPG-based approach to detect malicious attacks (i.e., jamming attacks, impersonation attacks, and intrusion attacks) in UAV-assisted computing networks.

3) Intelligent Reflecting Surfaces (IRS)-aided 6G Networks: IRS, or reconfigurable intelligent surface (RIS), is a surface with reflecting elements that can enhance network performance by changing the phase of these elements [39]. DRL can be used to optimize the placement of IRSs in 6G networks. By training an agent to determine the optimal configuration of IRSs, the signal-to-noise ratio (SNR) can be improved, resulting in better overall network performance. For example, DDPG has been used to increase the performance of an IRS-aided wireless network by maximizing the sum rate capacity via IRS phase shift and the beamforming matrix optimization [30]. The work [31] used IRS technology for optimizing resource allocation in mobile networks that have device-to-device (D2D) users. The authors introduced a decentralized DDQN algorithm for allocating resources to the users and a centralized DDQN for optimizing IRS. The proposed approach achieves near-optimal performance with reduced complexity and improved robustness. This results in higher transmission rates while satisfying QoS requirements.

UAV-mounted IRS can enhance signals from the base station to ground users [40]. For instance, an optimization method called FlyReflect, which employs a DDPG algorithm along with a mapping function, was proposed to enhance the data rate of a communication system that utilizes a UAV-installed IRS [32].

IV. Future Research Directions

As the field of DL and DRL continues to advance, there are numerous exciting opportunities for applying these techniques in 6G networks. In this section, we explore some potential areas of research that could help shape the future of this field.

A. DL/DRL in IRS-UAV-aided 6G networks

With the help of the IRS, current resource management techniques can further optimize the allocation of available resources and improve the overall performance of 6G networks. Therefore, it will be necessary to evaluate various DL models in situations where QoS requirements can change dynamically for accurate and flexible radio resource management. On the other hand, UAVs can offer vital services such as wireless communication, edge computing, and edge caching through the use of DL/DRL techniques. However, due to the limited resources of the UAVs, the need to develop energy-efficient DL/DRL model training and inference methods is becoming increasingly urgent, which remains an open and challenging problem. Additionally, the high mobility of UAV-assisted networks results in frequent changes in network topology and varying link states, posing challenges in maintaining stable end-to-end service quality. Therefore, it is imperative for researchers to consider these factors while designing DL/DRL-based network optimization algorithms for future UAV-assisted networks. Recently, some works focused on integration between IRS and UAV in wireless communication networks [32], [40]. It is challenging and interesting to investigate DRL-based optimization solutions in such heterogeneous wireless communication environments.

B. Decentralized/Distributed Learning

Federated/split/distributed learning is a decentralized approach to training DL models on data that is distributed across multiple devices or servers. It has the potential to enable more efficient and privacy-preserving DL in 6G networks, especially in scenarios where there is a need to handle significant volumes of data at the network's edge [41].

6G networks will be highly heterogeneous and involve multiple agents, such as base stations, edge servers, and mobile devices, that interact with each other. To effectively handle this complex system that operates on a large scale and in real-time, it may not be feasible to use single-agent DRL. Instead, multi-agent DRL (MADRL) is crucial for performance improvement. This requires establishing collaboration among agents, which can be achieved using a framework that combines centralized training and decentralized execution [42]. During the training phase, a single entity gathers relevant data from all agents, while during decentralized execution, each individual agent chooses an appropriate action based solely on its local observations of the environment. Therefore, further research in MADRL is essential for multi-agent network environments.

C. DL/DRL Enhancement

The unique requirements of 6G networks, such as ultra-low latency and high reliability, may require the development of novel DL architectures. Future research could explore new DL architectures specifically designed for 6G networks. Parameters can be tuned in DL/DRL, including the construction of hidden layers, the activation functions, the learning rate, and the buffer batch size. Hence, it is crucial to develop more efficient algorithms to decrease the training time and computational overhead. Transfer learning, where a model made from a different task is leveraged to learn the related target task, can be investigated [43]. Training data generation with GAN models can be applied to tackle the data imbalance problem [44]. GNN is a versatile model that can address extensive problems that involve non-Euclidean networks. GNN could be used to help allocate resources in dynamic 6G networks [20].

The DL/DRL models often dealt with the non-stationary problem by following common techniques such as experience replay, which required receiving a significant amount of raw data. As interest in MADRL increases, active cooperative learning should be encouraged to avoid asynchronous or independent communication between distant agents. In addition, explainable DL/DRL aims to make the trained models more transparent and interpretable by providing insights into how they make decisions. This is particularly important in safety-critical applications such as autonomous vehicles and UAVs. Developing explainable DL/DRL techniques tailored to 6G networks will be an important research direction.

V. Conclusion

This paper provided an overview of the applications of DL and DRL in 6G networks. Our survey of the current state-of-the-art studies in this field suggests that DL and DRL hold significant potential to address the stringent requirements of 6G wireless communication systems. Future research areas include the development of more efficient and accurate DL and DRL algorithms for 6G networks and the integration of these technologies with other emerging technologies. We expect to see continued growth and innovation in the applications of DL and DRL in 6G networks.

Acknowledgment

This research was supported by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2023-RS-2022-00156353) supervised by the IITP (Institute for Information & Communications Technology Planning & Evaluation)

References

[1] P. Yang, Y. Xiao, M. Xiao, and S. Li, "6G wireless communications: Vision and potential techniques," *IEEE Network*, vol. 33, no. 4, pp. 70–75, Jul. 2019.

[2] T.-H. Nguyen and J. J. Jung, "ACO-based traffic routing method with automated negotiation for connected vehicles," *Complex & Intelligent Systems*, vol. 9, no. 1, pp. 625–636, Feb. 2023.

[3] T.-H. Nguyen and J. J. Jung, "Swarm intelligence-based green optimization framework for sustainable transportation," *Sustainable Cities and Society*, vol. 71, p. 102947, Aug. 2021.

[4] J. J. Jung, L. V. Nguyen, L. Park, and T.-H. Nguyen, "Cooperative negotiation-based traffic control for connected vehicles at signal-free intersection," in *Intelligent Distributed Computing XV*. Springer International Publishing, 2023, pp. 297–306.

[5] C. Zhang, P. Patras, and H. Haddadi, “Deep learning in mobile and wireless networking: A survey,” *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2224–2287, 2019.

[6] A. Feriani and E. Hossain, “Single and multi-agent deep reinforcement learning for AI-enabled wireless networks: A tutorial,” *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 1226–1252, 2021.

[7] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016, http://www.deeplearningbook.org.

[8] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, S. Petersen, C. Beattie, A. Sadik, I. Antonoglou, H. King, D. Kumaran, D. Wierstra, S. Legg, and D. Hassabis, “Human-level control through deep reinforcement learning,” *Nature*, vol. 518, no. 7540, pp. 529–533, Feb. 2015.

[9] R. Dong, C. She, W. Hardjawana, Y. Li, and B. Vucetic, “Deep learning for radio resource allocation with diverse quality-of-service requirements in 5G,” *IEEE Transactions on Wireless Communications*, vol. 20, no. 4, pp. 2309–2324, Apr. 2021.

[10] B. Li, G. Verma, and S. Segarra, “Graph-based algorithm unfolding for energy-aware power allocation in wireless networks,” *IEEE Transactions on Wireless Communications*, vol. 22, no. 2, pp. 1359–1373, Feb. 2023.

[11] H. Huang, S. Guo, G. Gui, Z. Yang, J. Zhang, H. Sari, and F. Adachi, “Deep learning for physical-layer 5G wireless techniques: Opportunities, challenges and solutions,” *IEEE Wireless Communications*, vol. 27, no. 1, pp. 214–222, Feb. 2020.

[12] H. Xiao, W. Tian, W. Liu, and J. Shen, “ChannelGAN: Deep learning-based channel modeling and generating,” *IEEE Wireless Communications Letters*, vol. 11, no. 3, pp. 650–654, Mar. 2022.

[13] W. Kim, Y. Ahn, J. Kim, and B. Shim, “Towards deep learning-aided wireless channel estimation and channel state information feedback for 6G,” *Journal of Communications and Networks*, Jan. 2023.

[14] C. Liu, X. Liu, S. Li, W. Yuan, and D. W. K. Ng, “Deep CLSTM for predictive beamforming in integrated sensing and communication-enabled vehicular networks,” *Journal of Communications and Information Networks*, vol. 7, no. 3, pp. 269–277, Sep. 2022.

[15] C. Lee, H. Cho, S. Song, and J.-M. Chung, “Prediction-based conditional handover for 5G mm-Wave networks: A deep-learning approach,” *IEEE Vehicular Technology Magazine*, vol. 15, no. 1, pp. 54–62, Mar. 2020.

[16] S. K. Vankayala, S. K. S. Gollapudi, S. Singh, B. Jain, S. Yoon, and A. K. Bashir, “Deep-learning based proactive handover for 5G/6G mobile networks using wireless information,” in *2022 IEEE Globecom Workshops (GC Wkshps)*, IEEE. IEEE, Dec. 2022, pp. 461–466.

[17] M. Zhang, Y. Zhang, Q. Cen, and S. Wu, “Deep learning-based resource allocation for secure transmission in a non-orthogonal multiple access network,” *International Journal of Distributed Sensor Networks*, vol. 18, no. 6, p. 155013292211043, Jun. 2022.

[18] Y. Xiao, C. Xing, T. Zhang, and Z. Zhao, “An intrusion detection model based on feature reduction and convolutional neural networks,” *IEEE Access*, vol. 7, pp. 42 210–42 219, 2019.

[19] M. M. Hassan, A. Gumaei, A. Alsanad, M. Alrubaian, and G. Fortino, “A hybrid deep learning model for efficient intrusion detection in big data environment,” *Information Sciences*, vol. 513, pp. 386–396, Mar. 2020.

[20] M. Lee, G. Yu, H. Dai, and G. Y. Li, “Graph neural networks meet wireless communications: Motivation, applications, and future directions,” *IEEE Wireless Communications*, vol. 29, no. 5, pp. 12–19, Oct. 2022.

[21] G. Li, T.-H. Nguyen, and J. J. Jung, “Traffic incident detection based on dynamic graph embedding in vehicular edge computing,” *Applied Sciences*, vol. 11, no. 13, p. 5861, Jun. 2021.

[22] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial networks,” *Communications of the ACM*, vol. 63, no. 11, pp. 139–144, Oct. 2020.

[23] L. Ai, B. Tan, J. Zhang, R. Wang, and J. Wu, “Dynamic offloading strategy for delay-sensitive task in mobile-edge computing networks,” *IEEE Internet of Things Journal*, vol. 10, no. 1, pp. 526–538, Jan. 2023.

[24] S. Liu, C. Zheng, Y. Huang, and T. Q. S. Quek, “Distributed reinforcement learning for privacy-preserving dynamic edge caching,” *IEEE Journal on Selected Areas in Communications*, vol. 40, no. 3, pp. 749–760, Mar. 2022.

[25] J. Ye and H. Gharavi, “Deep reinforcement learning-assisted energy harvesting wireless networks,” *IEEE Transactions on Green Communications and Networking*, vol. 5, no. 2, pp. 990–1002, Jun. 2021.

[26] K. K. Nguyen, T. Q. Duong, T. Do-Duy, H. Claussen, and L. Hanzo, “3D UAV trajectory and data collection optimisation via deep reinforcement learning,” *IEEE Transactions on Communications*, vol. 70, no. 4, pp. 2358–2371, Apr. 2022.

[27] T. P. Truong, N.-N. Dao, and S. Cho, “HAMEC-RSMA: Enhanced aerial computing systems with rate splitting multiple access,” *IEEE Access*, vol. 10, pp. 52 398–52 409, 2022.

[28] T.-H. Nguyen, T. P. Truong, N.-N. Dao, W. Na, H. Park, and L. Park, “Deep reinforcement learning-based partial task offloading in high altitude platform-aided vehicular networks,” in *2022 13th International Conference on Information and Communication Technology Convergence (ICTC)*. IEEE, Oct. 2022, pp. 1341–1346.

[29] J. Tao, T. Han, and R. Li, “Deep-reinforcement-learning-based intrusion detection in aerial computing networks,” *IEEE Network*, vol. 35, no. 4, pp. 66–72, Jul. 2021.

[30] C. Huang, R. Mo, and C. Yuen, “Reconfigurable intelligent surface assisted multiuser MISO systems exploiting deep reinforcement learning,” *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 8, pp. 1839–1850, Aug. 2020.

[31] Z. Ji, Z. Qin, and C. G. Parini, “Reconfigurable intelligent surface aided cellular networks with device-to-device users,” *IEEE Transactions on Communications*, vol. 70, no. 3, pp. 1808–1819, Mar. 2022.

[32] T. P. Truong, V. D. Tuong, N.-N. Dao, and S. Cho, “FlyReflect: Joint flying IRS trajectory and phase shift design using deep reinforcement learning,” *IEEE Internet of Things Journal*, vol. 10, no. 5, pp. 4605–4620, Mar. 2023.

[33] T.-H. Nguyen and L. Park, “A survey on deep reinforcement learning-driven task offloading in aerial access networks,” in *2022 13th International Conference on Information and Communication Technology Convergence (ICTC)*. IEEE, Oct. 2022, pp. 822–827.

[34] H. V. Hasselt, A. Guez, and D. Silver, “Deep reinforcement learning with double Q-learning,” in *Proceedings of the AAAI conference on artificial intelligence*, vol. 30, no. 1. Association for the Advancement of Artificial Intelligence (AAAI), Mar. 2016.

[35] T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra, “Continuous control with deep reinforcement learning.” in *Proceedings of the 4th International Conference on Learning Representations (ICLR)*, 2016.

[36] V. D. Tuong, T. P. Truong, T.-V. Nguyena, W. Noh, and S. Cho, “Partial computation offloading in NOMA-assisted mobile-edge computing systems using deep reinforcement learning,” *IEEE Internet of Things Journal*, vol. 8, no. 17, pp. 13 196–13 208, 2021.

[37] D.-T. Hua, Q. T. Do, N.-N. Dao, and S. Cho, “On sum-rate maximization in downlink UAV-aided RSMA systems,” *ICT Express*, Mar. 2023.

[38] N.-N. Dao, Q.-V. Pham, N. H. Tu, T. T. Thanh, V. N. Q. Bao, D. S. Lakew, and S. Cho, “Survey on aerial radio access networks: Toward a comprehensive 6g access infrastructure,” *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 1193–1225, 2021.

[39] H. Park, T.-H. Nguyen, and L. Park, “Reconfigurable intelligent surface-assisted system models for uplink communications,” in *2022 13th International Conference on Information and Communication Technology Convergence (ICTC)*. IEEE, Oct. 2022, pp. 828–830.

[40] T.-H. Nguyen, H. Park, and L. Park, “Recent studies on deep reinforcement learning in RIS-UAV communication networks,” in *2023 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*. IEEE, Feb. 2023, pp. 378–381.

[41] H. Park, T.-H. Nguyen, and L. Park, “Federated deep learning for RIS-assisted UAV-enabled wireless communications,” in *2022 13th International Conference on Information and Communication Technology Convergence (ICTC)*. IEEE, Oct. 2022, pp. 831–833.

[42] T.-H. Nguyen and L. Park, “Multi-agent DRL-based task offloading in hierarchical HAP-LAP networks,” in *2022 13th International Conference on Information and Communication Technology Convergence (ICTC)*. IEEE, Oct. 2022, pp. 817–821.

[43] C. T. Nguyen, N. V. Huynh, N. H. Chu, Y. M. Saputra, D. T. Hoang, D. N. Nguyen, Q.-V. Pham, D. Niyato, E. Dutkiewicz, and W.-J. Hwang, “Transfer learning for wireless networks: A comprehensive survey,” *Proceedings of the IEEE*, vol. 110, no. 8, pp. 1073–1115, Aug. 2022.

[44] J. Huang, D. Hu, Z. Ding, and X. Wu, “Attack detection and data generation for wireless cyber-physical systems based on self-training powered generative adversarial networks,” *IEEE Wireless Communications*, vol. 29, no. 2, pp. 38–43, Apr. 2022.