Review

AI for UAV-Assisted IoT Applications : A Comprehensive Review

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Abstract: With the rapid development of the Internet of Things (IoT), there are dramatic increasing number of devices in the network, which causes the challenge that only using infrastructure such as based station cannot provide service with all devices with high quality. Therefore, due to their flexibility and economy, unmanned aerial vehicles (UAV) are widely used to increase the performance of IoT networks. UAVs can not only provide communication services for IoT devices in the absence of a network, but they can also perform video surveillance, cargo transportation, pesticide spraying, and other specialized tasks. However, due to the complexity of the scenario and the need for real-time decision making, it is challenging to schedule UAVs in the network using traditional optimization methods, and growing attention has focused on using AI to optimize UAVs in the network. In this paper, we focus on the AI-enabled UAV optimization method in IoT networks and give a comprehensive scope on what and how to use AI-enabled methods to increase the performance of UAV-assisted IoT networks. Moreover, a brief analysis of the challenges of using AI methods in IoT networks and some potential research directions are given.

Keywords: AI; UAV; IoT; mobile edge computing; reinforcement learning

1. Introduction

The Internet of Things (IoT), which consists of various sensors and lots of terminal devices connected by Internet, is dedicated to interconnecting everything and driving the industry. IoT is now widely used in various applications, such as environmental monitoring, industrial manufacturing, telemedicine, and etc., which promotes and improves people's lives. By 2050, there will be more than 170 billion devices connected to the Internet worldwide [1]. These hundreds of millions of devices will generate huge amounts of data that needs to be exchanged through wireless networks, putting enormous pressure on existing networks. Furthermore, since sensors and some terminals are limited by processing capability, a mass of data should be sent to the cloud or the edge servers for processing and analysis, preventing IoT devices from gaining value from collected data instantly and thus limiting IoT development.

With its flexibility, UAV can be deployed quickly, providing additional network resources to congested areas and remote areas without a network. Unmanned aerial vehicles (UAVs) can form self-organizing networks and act as flying base stations or relay nodes to provide network services and can be easily integrated into wireless communication networks [2]. In addition, by carrying a variety of sensing devices, UAVs can accomplish various tasks such as video surveillance, data collection, and cargo transportation, and they are immune to most disasters. According to the service demand, UAV can be deployed quickly with their high mobility and flexibility and it has been widely used in IoT scenarios such as smart agriculture, disasters, and smart cities [3,4]. Especially in some

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special situations, such as natural disasters like earthquakes and mudslides and operations in dangerous areas, UAVs can be rapidly deployed to complete tasks that are risky for people and provide communication and information support for rescue teams. It can be said that UAVs provide support for the applications of IoT and directs a promising research for future IoT. However, inefficient UAV system management, including communication resource management, energy management, and flight control, and energy limitations result in short UAV working hours and low mission performance, which seriously restricts the application of UAV for IoT applications.

Different from traditional optimization algorithms, AI is able to cope with complex, dynamic environments, is already widely used for system optimization and decision making, and is an important approach to further enhance the application of UAV in IoT. Artificial intelligence (AI) has been a hotly discussed topic since its emergence. With its powerful data processing and analysis capabilities, AI brings intelligence to devices and drives change in countless industries [5]. AI not only analyzes the ground information collected by IoT devices to help production and life, but also optimizes the performance of UAV communication networks, improves the safety of UAV flights, and brings autonomous decision-making capabilities to UAV [6]. Figure 1 shows the mainstream AI algorithms and their classification. AI can be divided into two categories: machine learning (ML) and non-machine learning (non-ML). ML is the method of obtaining models through data analysis and using them to predict unknown data, and it includes deep learning (DL) based on neural networks (NN), clustering algorithms such as k-means, decision trees, support vector machine, and linear regression and logistic regression algorithms for prediction. Among them, DL algorithms include models of deep neural networks such as deep neural network (DNN), convolutional neural network (CNN), recurrent neural network (RNN), generative adversarial network (GAN), and reinforcement learning (RL) and deep reinforcement learning (DRL) that can adapt to dynamic environments and make real-time decisions, such as Q-learning, deep Q-learning (DQN), deep deterministic policy gradient (DDPG), etc. Non-ML algorithms include early algorithms and expert systems based on semiotics and inference systems as well as heuristic algorithms such as genetic algorithms (GA), greedy algorithms, ant colony algorithms, etc. However, the application of AI needs adequate computing resource, which is lacking in UAVs.

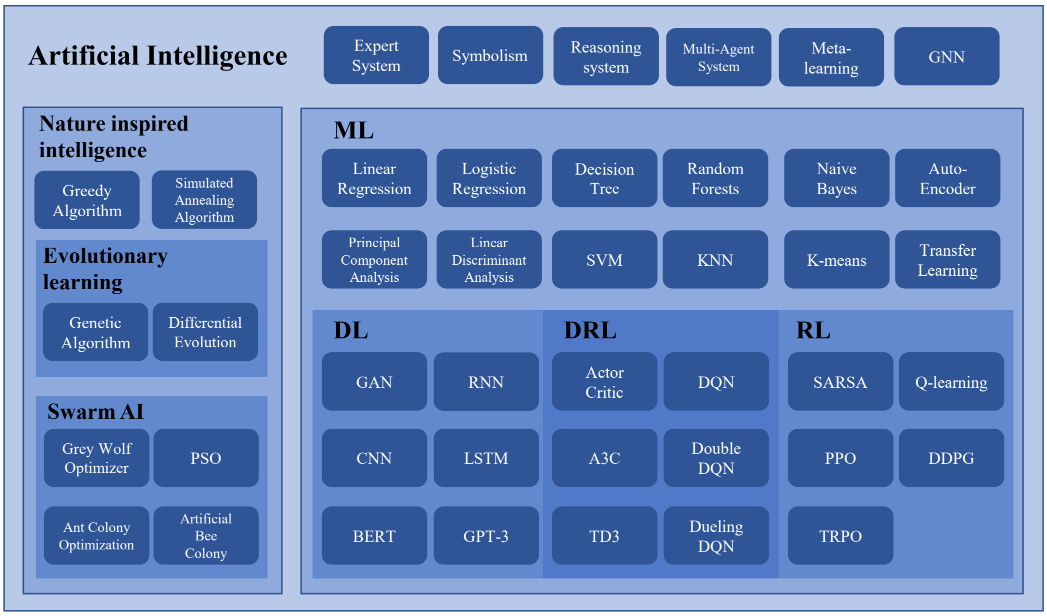

Figure 1. AI algorithms and classification.

Developed from cloud computing, mobile edge computing (MEC) brings computing and storage resources to the edge of the network, enabling IoT data to be processed at the edge of the network. It not only effectively relieves the pressure on the core network

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but also meets the needs of computing-intensive and delay-sensitive IoT devices, bringing computing power support for the development of IoT [7]. However, in remote areas with incomplete network construction and post-disaster areas with damaged terrestrial network facilities, IoT services still face the huge challenge of not having access to networks. Combining MEC and UAV is one possible solution. MEC server can provide computing power support for the execution of AI algorithms to improve the performance of UAVs and the ability of UAVs to provide services. UAVs can bring MEC services to areas lacking terrestrial networks with their flexibility. UAV-assisted and enabled MEC architectures have been studied in [8], where the UAV-assisted MEC architecture offloads the data to remote MEC servers for execution, while the UAV-enabled MEC architecture is equipped with an MEC server, which means that the tasks will be executed on the UAV. These two architectures solve the problem of the limited computing power of UAV. However, the UAV-enabled MEC architecture also carries the energy consumption of the MEC server, which becomes another energy burden for the UAV.

UAV-assisted and enabled MEC architecture brings a solution to the problem of IoT service stagnation in areas lacking terrestrial networks as well as network congestion. By enabling AI, the UAV-assisted and enabled MEC architecture is able to process large amounts of IoT data at the edge of the network, meeting the demands of latency-sensitive tasks while also improving the quality of service, energy efficiency, communication performance, and security of UAVs. The joint use of MEC, AI, and UAV for IoT has a promising future. However, the application process of AI still needs to consider the energy consumption limitations of UAVs, the optimization of dynamic network environments, and the design of lightweight AI algorithms to accommodate arithmetic limitations and meet latency requirements.

Table 1. Comparison of reviews on UAV, IoT and AI.

Year	Reference	IoT	UAV	UAV-assisted IoT issues					AI
				Trajectory Planning	Resource Allocation	Energy Efficiency	Security	Computing Offloading	
2016	[9]	✓	✓	✓		✓			
2018	[10]	✓		✓		✓	✓		
2020	[11]	✓				✓			
2020	[12]	✓		✓	✓	✓			✓
2019	[13]			✓	✓	✓		✓	✓
2020	[14]		✓	✓	✓				✓
2021	[6]			✓	✓	✓	✓		✓
2020	[15]	✓	✓						✓
2021	[8]	✓		✓	✓	✓	✓	✓	✓

There have been a lot of reviews on UAV, IoT, and AI, which are summarized in Table 1. The literature [9] provides a comprehensive survey of UAV communication and related issues and investigates the potential of UAVs to provide IoT services. In addition to the application of UAVs in the 5G and IoT domains, the literature [10] also focuses on security issues and promising solutions associated with the inclusion of UAVs in the IoT system. Similar to literature [9], the literature [11] summarizes the main technologies of UAVs and the applications and challenges of UAV-assisted IoT. However, the three aforementioned literatures focus on the application scenarios and related challenges of UAV in IoT and do not pay attention to the application of AI in UAV-assisted IoT. The literature [12] investigates the challenges faced when using non-terrestrial networks to provide services for IoT and analyzes the benefits of enabling AI techniques, but does not provide a comprehensive overview of the application scenarios for UAV-assisted IoT. The literature [13] details the application of ML techniques for physical layer, resource management, and network management in UAV-based communication. The literature [14] investigates the application of AI to UAV network localization, dynamic trajectory design, and resource allocation. The literature[6] deeply analyzes the ML, RL, and FL

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for UAV network enhancement and the future research directions. However, the above three literatures do not analyze the application of UAV and AI in IoT. The literature [15] discusses in depth the application of AI in UAV communication and focuses on UAV communication protocols, technologies, and architectures as well as UAV-assisted IoT application scenarios, but it does not summarize the tasks in UAV-assisted IoT and the corresponding AI solutions. The literature [8] provides insight into the application of UAV-enabled MEC in IoT and the application of ML to meet various constraints related to latency, task offloading, energy requirements, and security. However, the literature neglects the role of AI in UAV. Compared with the above literature, we have conducted a full and complete investigation into the application of AI in UAV and UAV-assisted IoT scenarios as well as the problems and solutions.

The structure of this review is shown in Figure 2. Chapter 2 discusses the problems in UAV communication networks and the application of AI in UAV and UAV communication networks. Chapter 3 describes the application scenarios of UAV-assisted IoT and the application of AI in UAV-assisted IoT. Chapter 4 summarizes the important problems in UAV-assisted IoT and the corresponding AI-based solutions. Chapter 5 analyzes the challenges and potential solutions when applying AI to UAV and UAV-assisted IoT. Finally, Chapter 6 concludes the paper.

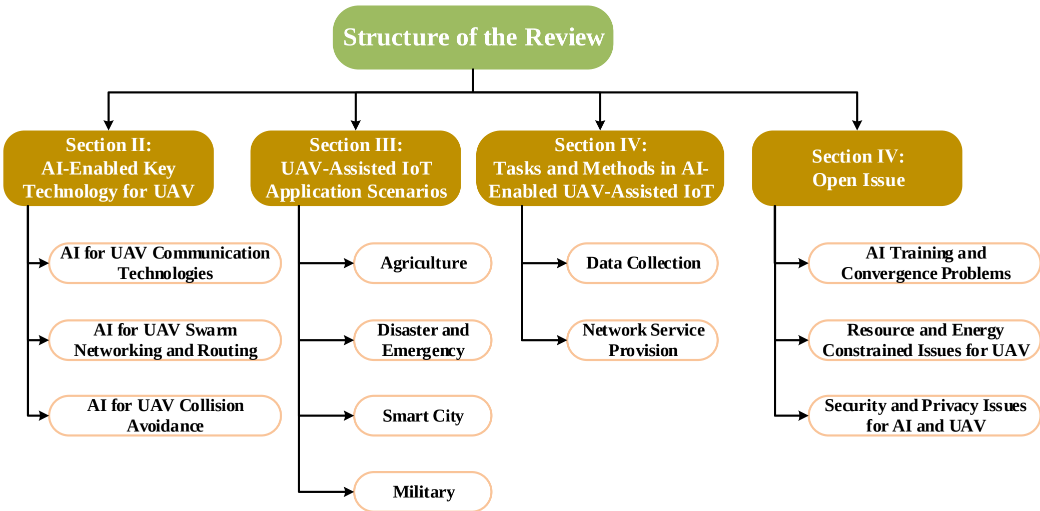

Figure 2. Organization of this article.

2. AI-Enabled Key Technology for UAV

There are some essential technologies to achieve high performance in UAV-assisted networks, such as communication technologies, networking and routing technologies, and UAV collision avoidance technologies. Communication technologies is used to increase the data transmission rate between two directly linked devices, such as UAV-to-UAV link and UAV-to-infrastructure link. Networking and routing technologies is used to decrease the delay caused by the multi-hop relay. Collision avoidance technology enables UAVs to fly without colliding, thus reducing the failure caused by UAV damage. The basic functions of AI are data analysis and data prediction. After continuous development, AI has been widely used in target detection, image recognition, speech recognition, natural language processing, intelligent control, and autonomous driving and has achieved great success in industrial, medical, and robotics fields. Applying AI to UAV can improve UAV communication quality through data analysis and prediction capability, perceive environment through graphics processing capability, and make UAV intelligent and autonomous through intelligent control capability.

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2.1. AI for UAV Communication Technologies

Flying in the air, UAVs offer a high degree of flexibility, ease of deployment, top-down coverage and immunity to natural disasters. Taking advantage of these benefits, UAVs are being used as a complement to ground networks to provide additional communication resources and are considered to be an important component of 6G networks.

Table 2. Comparison of common communication technologies for UAV.

Communication technology	Max data rate	Latency	Max range	Energy	A2A	A2G
Bluetooth	2Mbps	3ms	60m	Low(10mW)	Yes	No
ZigBee(802.15.4)	250kbps	20ms	100m	Low(1mW)	Yes	No
LoRaWAN	50kbps	>1s	15Km	Medium(100mW)	Yes	Yes
WiMAX	75Mbps	50ms	50Km	Medium(UE-200mW,BS-20W)	Yes	No
WiFi	500Mbps	50ms	250m	Medium(100mW)	Yes	Yes
4G	1Gbps	50ms	12Km	Medium(UE-10mW,BS-50W)	No	Yes
5G	10Gbps	1ms	200m	High(UE-400mW,BS-3000W)	No	Yes
6G	1Tbps	1ms	worldwide	–	No	Yes

Based on size, flight altitude and flight distance, UAV can be classified as small, medium and large. There are two important metrics for UAV communication, battery capacity and communication distance. Generally speaking, large UAVs have a larger battery capacity, which means the UAV can fly longer distances and perform more tasks. Moreover, large UAVs are generally designed for specific scenarios, such as military UAVs and Facebook Aquila UAV that provide communication services. In contrast, small UAVs have smaller battery capacities and need to be considered for their energy-constrained nature during use. In UAV communication networks, there are usually two types of wireless communication links, air-to-ground link (A2G) and air-to-air link (A2A). The A2G communication link refers to the communication link from the UAV to the ground equipment, including the UAV to ground station links and the UAV to ground users links. The A2A communication link refers to the communication links between UAVs. The UAV communication channel model considers the large-scale fading caused by path loss and the small-scale fading caused by multipath interference. Compared with the A2A channel, the A2G channel will produce larger shadow fading and small-scale fading [16]. Moreover, considering the high mobility of the UAV, attention needs to be paid to Doppler spread as well as the effect of aircraft shadowing [17]. Equipped with communication protocols, UAVs can communicate with ground users and other UAVs. At present, the communication protocols commonly used in UAVs are Bluetooth, ZigBee, LoRaWAN, WiMAX, WiFi, 4G, 5G and 6G, all of which have different performance in terms of data rate, delay, energy consumption, transmission distance, etc. For example, Bluetooth, ZigBee and LoRaWAN are all low-power wireless communication technologies, and among these, Bluetooth can achieve the best data rate and latency, ZigBee can achieve the lowest energy consumption, and LoRaWAN has the longest communication distance. WiFi is a widely used wireless fidelity technology based on the IEEE 802.11 standard, which includes two different modes of operation: the infrastructure mode and the ad-hoc mode [18]. Thus, Wi-Fi can be used for both A2A communication and A2G communication. The typical Wi-Fi has a maximum coverage of 100 meters, adding with the directional enhanced antenna and the automatic tracking communication platform, the coverage range can extend to 500 meters [19]. As the most widely used mobile technology, 4G offers high speed and low latency with a guaranteed long range of service. However, as the signal frequency increases, 5G loses the ability to propagate signals over long distances while

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gaining improved performance in terms of data rate, bandwidth, and latency, and further increases the energy consumption of devices. 6G aims to provide a globally ubiquitous network service, which is not only an iteration of communication technologies, but also a heterogeneous convergence of multiple networks and intelligent control of all networks. Specific information about these communication technologies can be found in Table 2. Considering the engineering requirements for data rate, delay, and energy consumption, as well as the energy-constrained characteristics of UAVs, the appropriate A2A and A2G communication technologies should be selected by combining the engineering requirements and the characteristics of each communication technology.

In practical applications, there are often multiple signals in the air, with varying degrees of interference between them. Besides, in some energy-constrained scenarios, such as sensor networks in remote areas, the energy consumption of the system is further limited. There has been a lot of research on AI to improve network performance. AI can solve the signal interference problem well and also reduce network energy consumption, guarantee network security, and improve network performance. The application of AI in wireless communication technology is shown in Figure 3. In the following, we will introduce in detail the application cases of AI in communication technologies to promote UAV communication.

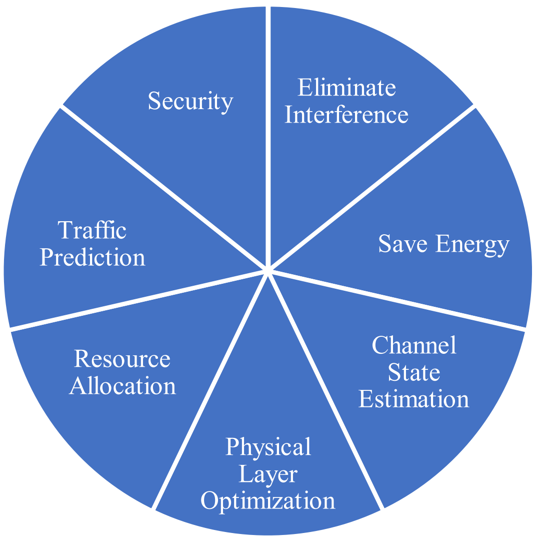

Figure 3. Application of AI in wireless communication technology.

Bluetooth and ZigBee are low-power, low-cost, short-range wireless communication technology based on IEEE 802.15.1 and IEEE 802.15.4, respectively. They can provide low to medium data rate service for A2A and A2G links for ranges between 10 to 100 meters [20]. The shared frequency bands between Bluetooth, Zigbee, WiFi, and other signals cause unavoidable interference. To avoid interference, a supervised learning-based channel quality evaluation algorithm is proposed in the literature [21] to predict channel quality, where gated recursive units are used to extract interference information on each channel and identify the top 20 channels for data transmission based on the past received signal strength metrics of the channel. And a novel loss function combining classification loss and ranking loss was proposed to improve neural network performance. Experimental results show that the proposed network is lightweight and resource-friendly, and the proposed method outperforms channel selection schemes such as Mask 19. The length of the connection interval (CI) and the number of packets transmitted per CI affect the energy efficiency and QoS of Bluetooth. A larger CI corresponds to a longer network lifetime, but may negatively affect the QoS specified as packet delay. A higher number of packets transmitted per CI corresponds to a higher QoS, but it consumes more energy, reducing network lifetime. To extend the network lifetime with guaranteed QoS, a Q-learning based Bluetooth scheduling algorithm is proposed in literature [22] to dynamically adjust the length of Bluetooth CI and the number of packets transmitted per CI. The reward function is designed so that the scheduling algorithm learns to satisfy both energy efficiency and quality of service requirements. Numerical results show that the method greatly outperforms random and fixed action schemes in terms of network lifetime while also ensuring QoS and stability. For ZigBee, it is also important to achieve similar interference cancellation as Bluetooth to ensure that ZigBee is protected from interference attacks. In order to decode ZigBee signals in the presence of interference, the literature [23] proposes to use a neural network as a linear spatial filter to suppress interference and to accelerate the training of the neural network using the inherent relationship of its weights, which can guarantee ZigBee communication even when the interference signal is 20 dB stronger than the ZigBee signal.

LoRaWAN is another low-power, low-data-rate, but long-range communication technology that can reach several kilometers [24]. It can be used for both A2A and A2G communications. As a low-power wide-area network (LPWAN), low power consumption and high connectivity are essential for LoRaWAN. The choice of transmission parameters is decisive for network energy consumption. In order to reduce energy consumption and improve the performance of LoRa networks, transmission power values need to be automatically adjusted according to network requirements and link conditions. The literature [25] proposes a strong transmission parameter selection algorithm based on EXP3 to select the optimal propagation factor and transmission power to reduce the energy consumption of the network. A large number of devices access can cause packet conflicts and degrade the network communication performance. The literature [26] proposes a LoRaWAN channel selection method based on lightweight decentralized reinforcement learning to choose the appropriate channel based on acknowledgement information, thereby effectively avoiding conflicts between LoRa devices with low computational complexity. Similar to [26], to avoid conflicts among LoRa devices, the literature [27] proposes and evaluates a LoRaWAN physical layer transmission parameter assignment algorithm based on double deep Q-learning, which selects the spreading factor and power and can ensure less conflicts and better performance.

The optimal parameters for WiFi link configuration depend on the perceived channel quality based on signal strength, channel noise, and external interference. In order to maximize the link layer performance, literature [28] uses a deep neural network-based Gaussian process regression to predict the link layer throughput and a model predictive control-based approach to find the link configuration parameters that optimize the overall link layer performance. Compared with high-throughput adaptation mechanisms, DNN-based methods can significantly improve link-layer performance. DNNs are also used to control the contention window of the WiFi 6 system in [29], where DNNs are trained by data generated from the Wi-Fi 6 simulation system, using loss functions to improve the accuracy of the model in predicting the system throughput, latency, and retransmission rate, and searching for the optimal configuration of CW under different network conditions based on the prediction results. This DNN-based WiFi control strategy achieves significant improvements in system throughput, average transmission delay, and packet retransmission rate. In order to improve the efficiency of downlink MU-MIMO-OFDMA transmission in 802.11ax networks, a deep learning-based channel detection (DLCS) and deep learning-based resource allocation (DLRA) approach is proposed in the literature [30]. DLCS utilizes the compression capability of DNN to compress the frequency domain CSI during the feedback process. Then, based on the limited CSI, the AP infers CSI over all tones using well-trained DNNs, reducing the channel sounding overhead of the 802.11 protocol, and the AP uses the uplink channel to train the DNN for the downlink channel, making the training process easy to implement. DLRA uses DNNs to solve the mixed-integer power allocation problem to improve system throughput and enable APs to obtain near-optimal solutions in polynomial time. The coexistence of LTE and WiFi can severely degrade WiFi performance. To protect WiFi communication, the literature [31] proposes a CNN-based distributed spectrum management framework, in which CNNs are used to identify the signatures of each technology and report the spectrum occupation of each

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channel, and then avoid them by changing the Wi-Fi operating center frequency based on the detected harmful wireless networks to improve Wi-Fi performance.Âă Utilizing the ability to cope with large-scale data, DL is shown to improve the performance of intrusion detection systems (IDS) [32]. The literature [33] proposes a fully unsupervised intrusion detection method based on K-means that can detect attacks without a priori information about the data labels, where stacked auto-encoder is used to capture complex information in lower-dimensional features than the original features, thereby enhancing the clustering effect of the K-means algorithm. The clustering results of K-means have only two classes that represent benign and malicious data. The method is able to classify simulated attacks in WiFi networks with a detection rate of 92%.

Relying on cellular networks, LTE (Long Term Evolution) can provide secure, reliable, and wide coverage A2G communications [34]. With LTE-A (Long Term Evolution Advanced), the average throughput of both uplink and downlink is further increased [35]. Not only the coexistence of LTE and WiFi but also the coexistence of the Narrowband Internet of Things (NB-IoT) and LTE can interfere with LTE systems. An iterative sparse learning algorithm called sparse cross-entropy minimization (SCEM) is proposed in [36] to eliminate the narrowband interference, and experimental results demonstrate that the SCEM algorithm outperforms sparse Bayesian learning based methods. Due to the dependence on the cellular network, the impact of handover on network quality must be considered. To improve the quality of experience (QoE) of the users, a supervised learning approach-based on NNs is used for optimal handover cell prediction [37]. Obtaining the current data rate is important for network management and resource allocation. However, considering the energy wastage associated with long-term observation of wireless links, an ANN-based algorithm is proposed in [38] to predict the data rate of LTE links to avoid congestion and save energy.

WiMAX is a cost-effective broadband wireless access technology based on the IEEE 802.16 standard, which covers longer distances than Wi-Fi [39]. WiMAX can provide A2G communications, capable of handling high-quality voice and video streams and providing a high user experience [40]. The research on AI in WiMAX is mainly focused on two aspects: channel prediction and bandwidth allocation. Accurate prediction of wireless channel quality is important to improve network performance. The literature [41] proposes an encoder-decoder based sequence-to-sequence DL model that predicts the future channel quality based on the past channel quality. Experimental results demonstrate that the RL-based model outperforms the auto-regression model and the linear regression model in terms of prediction accuracy. Fair bandwidth allocation for different types of traffic with limited bandwidth is important to ensure the quality of service for applications in WiMAX networks. In [42], a reinforcement learning-based algorithm is proposed to learn the traffic demand in the network and make an efficient bandwidth allocation to meet the QoS requirements of the application.

5G is committed to providing ubiquitous connectivity and can meet the higher demand for services in terms of data rate, bandwidth, latency, and other metrics [43]. With its highly flexible and easy-to-deploy nature and robust line-of-sight connectivity links, UAV can be used as a complement to ground networks to extend coverage or as relays to collaborate with ground network communications and are expected to be a key part of 5G to achieve ubiquitous connectivity [44]. With 5G rather than other communication technologies, UAVs can serve a wider range of applications. However, the complexity of the network architecture and the diversity of service requirements make it difficult to optimize the 5G network with traditional approaches. With powerful computing power and the ability to interact with the environment, AI is expected to be an important method to improve 5G performance [45]. AI has been widely used in the physical layer optimization of 5G networks to improve network performance. Non-orthogonal multiple access (NOMA), massive multiple input multiple output (MIMO), and millimeter wave (mmWave) are key technologies to improve 5G performance, and the feasibility of using DL to enhance these technologies has been discussed in [46,47]. And good performance can be obtained

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in scenarios such as channel estimation, coding and decoding, and massive MIMO. In [48], ANNs are used for channel state information (CSI) estimation, which improves network throughput and saves uplink energy by making accurate CSI predictions. The literature [49] also employs the integration of CNN and long short-term memory (LSTM) networks to predict CSI with high accuracy using historical data. Specifically, the raw data are first preprocessed and converted into CSI information images. Then, the CSI information images are fed into the CNN network to extract frequency representative vectors. Finally, the state representative vectors are fed into the LSTM network, and the predicted state vectors are output. Applying AI to radio resource allocation techniques is another important research direction for using AI to optimize the physical layer of 5G networks. To meet the diverse service requirements, the literature [50] uses NNs to jointly optimize the power and bandwidth resource allocation and thus minimize the total power consumption of the base station, where a cascading structure of NNs is proposed to solve the problem that fully connected NNs cannot fully guarantee the QoS requirements. The first NN is used for optimal bandwidth allocation, and the second NN outputs the transmit power required to meet the QoS requirements for a given bandwidth allocation. Simulation results demonstrate that cascaded NNs outperform fully connected NNs in terms of QoS guarantees. In the literature [51], a Q-learning-based power and resource allocation algorithm is proposed to improve the latency and reliability of URLLC users and the throughput of eMBB users when considering heterogeneous traffic with different QoS requirements. The algorithm achieves a significant improvement in throughput for eMBB users and a slight decrease in latency for URLLC users. To cope with congestion in ultra-dense networks (UDNs), the literature [52] uses deep LSTM learning techniques to locally predict the traffic load of UDN base stations and executes appropriate action policies based on the prediction results a priori to mitigate congestion in an intelligent manner. Simulation results show that the scheme outperforms the conventional approach in terms of packet loss rate and throughput. Also in response to the increase in traffic load, the literature [53] proposes request prediction methods based on DNN and LSTM, respectively, where DNNs and LSTMs trained on mobile network traffic datasets are used to predict the rate of additional user requests, thereby reducing the delay in deploying virtual network functions. Simulation results confirm that both DNN and RNN-based solutions are more effective than threshold-based solutions in terms of latency when responding to traffic variations. The rapid growth of IoT devices has put enormous pressure on cybersecurity. To counter these network attacks, the literature [54] uses CNNs to detect anomalous network traffic to create a more proactive, end-to-end defense for 5G networks, where network traffic is converted into images that can be analyzed by CNNs for CNN training as well as anomaly detection. In using CNNs to collect and analyze normal and anomalous network traffic from a simulated environment, the method identifies benign traffic with 100% accuracy and anomalous traffic with 96.4% detection rate.

2.2. *AI for UAV Swarm Networking and Routing*

UAV swarm consists of multiple UAVs, which expands the network coverage and improves the stability of the network compared to a single UAV system. Current wireless network architectures for UAV swarms can be divided into infrastructure-based networks (IBN) and ad-hoc-based FANET networks [55]. These two UAV communication network architectures are shown in Figure 4. Infrastructure-based UAV network architecture relies on ground infrastructure to provide relay services between UAVs and UAVs cannot communicate directly with each other [15]. In FANET, UAVs can communicate with each other directly or indirectly, without the help of ground infrastructure. For FANET, the topology of the UAV swarm has a significant impact on communication efficiency. Common topologies are star, mesh, and multi-layer networks. In a star network, all UAVs communicate with ground nodes or other UAVs through a specific UAV, which may lead to network congestion. Mesh networks, in which nodes are interconnected, have higher flexibility and reliability compared to star networks. However, due to the presence of multiple routes, an efficient routing protocol is needed to select the best path as well as adapt to changes in the network structure [56]. In addition, considering the variable topology of UAV networks due to the mobility of UAVs, the signal interference among UAVs, and the network management problems caused by the energy limitation and resource differences of UAVs, real-time dynamic and efficient routing protocols and network management solutions are needed to ensure the quality of service of UAV networks instead of traditional static routing protocols and network management solutions. The conventional routing protocols include static routing protocols, proactive routing protocols, reactive routing protocols, hybrid routing protocols, location-based routing protocols, hierarchical routing protocols, and probabilistic routing protocols [57]. Most of these routing protocols are not appropriate for UAV networks with high mobility because they are designed primarily for low-speed self-organizing networks with slow topology changes. AI algorithms, especially ML algorithms, are able to make optimal decisions by learning about the environment, such as network topology, channel state, and other information. Applying AI algorithms to routing protocols can address the dynamic nature of the network. The AI-enabled routing protocols are topology prediction-based routing protocols and adaptive learning-based routing protocols. Topology prediction-based routing protocols forecast the link and network topology states using ML techniques to produce better routing policies and increase the stability and throughput of the network. In addition to continuously learning the environment, adaptive learning-based routing protocols also learn to maximize key network performance parameters, including network congestion, throughput, energy consumption, network longevity, and fairness, to generate a routing policy that is suitable for our purposes. Q-learning algorithms are frequently used in adaptive learning-based routing protocols. Examples include QoS-aware Q-routing, which can outperform ad-hoc routing algorithms while meeting QoS requirements, and Q-learning-based multi-objective optimized routing protocols, which can achieve higher packet arrival rates than the Q-learning-based routing algorithm while using less energy and delaying communications [58,59].

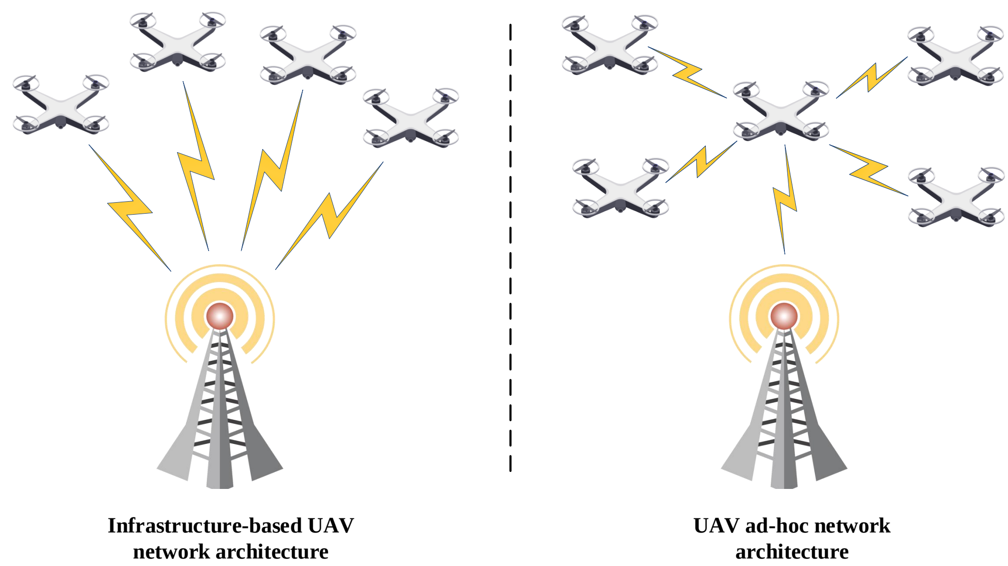

Figure 4. UAV communication network architectures.

In addition to dynamic network topology, during the application of UAV swarms, attention should also be paid to the allocation of network resources with the goal of improving the efficiency of network services and dynamically planning the spectrum resources of UAVs according to the needs of the scenario. For example, in order to maximize the spectrum resources available to the UAV swarm and prevent interference, the literature [60] focuses on the resource allocation problem of UAV swarm networks by identifying the ideal frequency band for each UAV. However, it ignores the energy management issue

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of UAVs and does not dynamically arrange the spectrum resources according to demand, resulting in a short operation cycle for the UAV swarm network. Therefore, the UAV swarm network should dynamically allocate spectrum resources according to the application requirements to maximize the energy efficiency of UAVs and prolong the network lifetime. In addition, due to the highly dynamic and complex UAV swarm service scenarios, using traditional algorithms to solve UAV swarm network problems takes a lot of time and cannot achieve real-time processing and decision-making. The use of artificial intelligence algorithms, especially machine learning algorithms, to solve network problems is a current research hotspot. AI algorithms are able to adapt to the dynamics and complexity of the UAV swarm environment and make real-time decisions. Literature [61] suggests a digital twin-based intelligent collaboration framework for UAV swarms to better learn the optimal decisions from the network environment by fusing digital twin techniques with reinforcement learning techniques. Digital twin and ML have become very popular topics in recent years. The effectiveness of the suggested approach is demonstrated in the intelligent network reconfiguration of UAV swarms in time-varying environments. Experiments demonstrate that the algorithm can select the optimal network model in different scenarios. In order to provide broadband wireless communication, millimeter waves are introduced to UAV swarms, but this also creates issues with millimeter beam misalignment due to UAV movement and interference among UAV swarms. In order to manage spectrum resources and UAV energy consumption with improved flexibility and efficiency, a new resource management architecture was developed in [62] as a solution to this challenge. And the effectiveness of the proposed spectrum management architecture is validated in five potential scenarios.

2.3. AI for UAV Collision Avoidance

Collision avoidance technology is an important issue that needs to be considered during the flight of UAV. UAVs should avoid collisions not only with other UAVs but also with various obstacles such as buildings, birds, trees, etc. In general, UAV collision avoidance techniques include three steps: obstacle sensing, collision prediction, and collision avoidance [63]. The process of a UAV gathering information about obstacles is called obstacle sensing. Through cooperative obstacle sensing techniques, information about the UAV's condition as well as information about the surrounding obstacles can be shared between UAVs. However, existing methods can only be used between UAVs that use the same protocol and cannot acquire information about obstacles in the surrounding environment. In order to obtain information about obstacles in the surrounding environment, the usual approach is to use sensors to sense the environment and to obtain the location of obstacles through imaging and positioning techniques.

For a UAV swarm, position information can be shared, and internal collisions can be avoided by planning the flight path of each UAV within the swarm.Âă For instance, the literature [64] proposes a DRL-based formation flight control for navigation for effective UAV swarm construction. The collision rate of successful formation UAVs is reduced to 3.4% without colliding with other UAVs. However, for the UAVs outside the UAV swarm, since the flight trajectory of other UAVs cannot be known, the flight trajectory must be adjusted according to the real-time dynamic environment to avoid collision. After obtaining information about the UAV trajectory and the surrounding obstacles, it is possible to predict whether a collision will occur by using a collision prediction method. The collision avoidance algorithm then performs a collision avoidance operation, typically by devising a brand-new collision-free path. Numerous other academic works also simultaneously study collision avoidance and prediction. In [63], collision prediction algorithms are classified into two main categories: trajectory fitting methods and ML methods. The trajectory fitting function often cannot achieve accurate prediction because the environment is too complex during the movement of UAVs. Fortunately, ML algorithms can make more accurate trajectory predictions by extracting features. However, the use of ML algorithms generates high energy consumption, which is not very friendly to energy-constrained

UAVs. Among the ML algorithms, CNNs are good at extracting features, while RNNs and reinforcement learning can acquire knowledge from past experience, and these features enable them to make more accurate trajectory prediction. In [65], LSTM was used to predict the motion of obstacles, and an uncertainty-aware multi-agent dynamic collision avoidance algorithm based on nonlinear probabilistic velocity obstacles was proposed that can avoid obstacles that the optimal reciprocal collision avoidance algorithm cannot avoid. Object detection(OD) and deep reinforcement learning (DRL) are used to solve the problem of collision-free autonomous UAV navigation supported by simple sensors in [66], where OD is used to provide accurate environmental observations for DQN and DQN is used to make optimal flying decisions. Compared to the algorithm using DRL alone, OD+DQN not only enables collision-free UAV flight but also reduces the flight distance. The literature [67] proposes a two-stage reinforcement learning strategy to solve the UAV collision avoidance problem under imperfect perception, where the first stage uses a supervised training method with a loss function to optimize the collision avoidance strategy and the second stage uses a policy gradient to refine the collision avoidance strategy. This two-stage reinforcement learning has increased performance in terms of success rate and trajectory length compared to conventional reinforcement learning. In [68], UAVs are used to collect data from ground devices, and Q-learning is used to help UAVs avoid collisions without knowing the trajectories of other UAVs. This scheme allows the UAV to avoid collisions and can reduce the path length of the UAV when collecting data. Energy consumption is another important factor to consider for UAVs, and reinforcement learning algorithms will consume a lot of energy during their execution.

3. UAV-Assisted IoT Application Scenarios

As illustrated in Figure 5, there are a lot of application scenarios for UAV-assisted IoT. For example, UAVs can monitor crop growth, spray pesticides, and also automate farms for smart agriculture. In disasters and emergencies, UAVs can provide emergency communication services, deliver supplies, and monitor the environment. UAVs can also empower smart cities by supporting video surveillance, smart transportation systems, and healthcare. In the modern battlefield, UAVs are of tactical importance. In addition to providing communication services as well as reconnaissance of the battlefield, there are many specific military UAVs used to perform military missions. With the support of AI, UAVs can complete various IoT tasks more efficiently.

3.1. Agriculture

Food is the most essential element of people's lives. According to a survey by [69], total global food demand is expected to increase by 35% to 56% by 2050 compared to 2010. In order to cope with the increasing food demand, the development of agricultural technology is needed to drive the increase in food production. In addition, the Internet of Things will enable real-time monitoring and management of arable land, bringing a new paradigm to the development of agriculture [70]. Using sensors to obtain environmental information such as images and temperatures, and then analyzing the data and making immediate decisions through big data or AI methods, applying IoT to agriculture can increase productivity and yields and reduce costs, providing support for smart and precision farming. However, the high construction cost of terrestrial networks and the limited network services due to fixed terrestrial network equipment severely limit the application and development of IoT in agriculture. Compared with expensive terrestrial and satellite networks, drones are more economical and flexible to deploy, perform data collection, and provide high-quality network services on demand. UAVs are typically used in agriculture for crop monitoring, drug spraying, etc. Specifically, they perform data collection, network provisioning, and special agricultural tasks. In performing data collection, the UAV first collects information from ground sensors or through sensors equipped with the UAV. The data is then transferred to a computing center or processed on the UAV and analyzed by algorithms to arrive at decisions. AI algorithms can be applied to the flight control, data

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Figure 5. UAV-assisted IoT application scenarios.

processing, and decision-making processes of UAVs, which can speed up data processing and make immediate decisions. Deep learning techniques, especially CNNs, have powerful image processing capabilities. Combining DL with UAVs can be used in smart agriculture for vegetation identification, classification, and segmentation, crop counting and yield prediction, crop mapping, weed detection, and the detection of crop diseases and nutrient deficiencies [71]. In addition, UAVs can also be used to spray pesticides to further reduce labor costs and realize agricultural automation. AI can also be used to plan UAV operation strategies to improve UAV work efficiency. In order to allow UAVs to efficiently and cost-effectively collect farm data for further analysis and decision-making, the literature [72] uses Q-learning to plan UAV trajectories in intelligent farm remote sensing, a scheme that collects data with the lowest energy consumption as well as the least time delay. However, a more practical model needs to be considered in future work.

3.2. Disaster and Emergency

Disasters such as earthquakes usually result in damage to infrastructure such as houses and roads. The absence of available communication facilities can cause great inconvenience to rescue operations. Unlike ground-based networks, UAVs are immune to most natural disasters and can be flexibly deployed to provide communication services to disaster areas. In addition, UAVs can carry cameras and sensors to obtain site conditions and sense environmental information, which can help people analyze disaster situations as well as perform rescue missions. However, limited by energy, UAVs need to ensure energy efficiency and thus extend their service time when providing communication services and performing special tasks. Moreover, UAVs work in a dynamic environment, which is difficult for traditional algorithms to cope with. Using AI to cope with the problem of optimizing resource allocation for UAVs not only adapts well to the dynamic environment but also brings autonomy to UAVs and enhances the automation of UAVs. In order to improve the efficiency of UAVs in performing tasks as well as energy efficiency, the

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literature [73] considers a scenario where a multi-mission UAV provides tasks such as material transportation and communication services in a post-disaster area and uses a greedy algorithm and an algorithm based on an insertion algorithm to plan the mission. Both heuristic algorithms can achieve savings in the time required to plan the UAV compared to the optimal algorithm while ensuring good performance, thus enabling a fast response to unexpected situations. In addition, UAVs can be used for airdrops of supplies in disaster areas and forest fire fighting. It is worth noting that ground communication facilities may be damaged due to disasters, and communication services are crucial for post-disaster reconstruction efforts. UAVs can be used as flying base stations to provide communication services in disaster areas. For example, in [74], an emergency communication system using a UAV as a flyingÂăbase station to assist ultra-dense networks is proposed, and a DQN-based resource allocation scheme is proposed to maximize system energy efficiency while ensuring user communication quality to cope with system emergencies when communication resources are insufficient. To extend network coverage, multiple UAVs often form swarms of UAVs to provide communication services to disaster areas. However, ground users such as escapees and rescuers are usually constantly moving, which requires the UAV swarm network to be able to adapt the network structure to the ground personnel activities in order to provide as many services as possible. The literature [75] proposes a mobility model for simulating the movement of victims in disaster situations and combines Jaccard distance and simulated annealing algorithms to deploy UAV swarm networks, which avoid network disconnections while increasing the number of users served.

3.3. Smart City

Although there is no precise definition of "smart city," we can consider it an urban optimization solution that uses advanced information and communication technologies, IoT technologies, big data, and AI to empower cities, thereby facilitating city management and providing convenience to citizens [76]. Typical smart city application scenarios include smart transportation systems, smart city monitoring, smart healthcare, smart grid, smart education, etc [77]. The implementation of smart cities is important for energy savings and emission reduction, environmental protection, and sustainable urban development. There are many uses for UAVs in smart cities, which can be used to collect sensor information, transport goods, and monitor the city. The following are three scenarios that will introduce the use of UAVs in smart cities: urban surveillance, intelligent transportation systems, and healthcare.

3.3.1. Surveillance

With the increasing population of cities, more resources need to be invested to enhance urban security and thus protect people's living standards. In addition to placing security personnel on guard, major cities have deployed advanced video surveillance systems to monitor the occurrence of abnormal situations in the area [78]. However, security personnel cannot do real-time monitoring, and the labor cost is relatively high. Video surveillance systems can do real-time monitoring, but it is difficult to effectively identify various hazardous situations with a fixed monitoring perspective. UAVs are highly flexible and can track and monitor targets in a comprehensive manner. Moreover, UAVs can be deployed quickly and can effectively respond to unexpected situations as well as make up for the blind spots of the video surveillance system. The combination of UAVs and video surveillance systems can further improve urban security.

To be able to accurately identify and track anomalies, video surveillance systems as well as UAVs must have image recognition technology, which is usually implemented by AI algorithms. For example, CNN and OpenCV are widely used models in the field of image recognition. In addition, AI is able to pre-process image data to reduce redundant data for transmission, enable planning of UAV paths, and improve surveillance efficiency and energy efficiency. However, computationally intensive tasks like data processing can place a huge energy and computational burden on UAVs. The combination of the UAV

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and the MEC server provides a solution to this dilemma. Data processing tasks can be performed either by UAV transmission to a remote server or on a UAV equipped with MEC server. The literature [79] investigates the question of whether image processing should be performed locally or offloaded to the MEC server when using a cluster of UAVs for crowd monitoring and facial recognition. Experimental results show that offloading the image processing tasks to the MEC server can reduce energy consumption and processing time by more than 100 times. Most surveillance systems employ a single data source for target localization, and the utilization of multi-UAV sensor networks is uncommon but has enormous potential. The literature [80] presents a novel multi-UAV surveillance system for multi-target identification and tracking, including a video image-based moving target identification method, a collaborative UAV task assignment algorithm based on group intelligence optimization, and a localization model based on machine learning and data fusion methods. Machine learning is first used to extract the topology of the data based on the multi-source data collected by UAVs and sensors to establish a mapping between the data and the environment. The target's location is then estimated using mapping based on the target's relevant data. Finally, pigeon-inspired optimization is used to coordinate multiple UAVs, taking energy constraints into account to determine which UAV is assigned to perform the localization and tracking tasks. The system is empirically validated to have high localization and tracking accuracy. UAVs are utilized for crime prediction in [81]. These UAVs are classified into three classes, which are utilized for sensing information, computational analysis, and deterrence. First, sensing UAVs acquire data from sensors, such as pictures and sounds, and send it to computing UAVs. Then, trained ML models are used by computational UAVs to anticipate potential crimes. Finally, depending on the forecast findings, deterrent UAVs will travel to the respective locations for observation. The experiment shows that when the deterrent separation is 1280 meters, 20 UAVs can discourage virtually all offenses. To provide a reliable surveillance system using a swarm of UAVs, a collaborative model-free multi-agent deep reinforcement learning-based algorithm has been proposed in the literature [82], which finds the optimal trajectory within the surveillance area in order to optimize the energy consumption and the number of users that can be monitored.

3.3.2. Intelligent Transportation Systems

Intelligent transportation systems (ITSs) are an important part of smart cities. With the development of information and communication technology, autonomous driving technology, and connected vehicle technology, ITSs are also progressing and moving toward the automation of transportation systems [83]. However, current traffic systems still require human resources, such as traffic police, to be on the scene to provide support in case of road congestion or accidents, which often requires a long response time. UAVs are able to be quickly and adaptably deployed to provide services for some ITS automation scenarios, such as using UAVs to collect road data for ITS decision-making and scheduling, providing quick response to emergencies like traffic accidents and providing on-site information, and acting as flying base stations to provide communication services for in-vehicle self-organizing networks [84].

To improve the timeliness of UAV-assisted road information collection for telematics, the literature [85] introduces the concept of AoI to keep the information fresh and uses the DDPG algorithm to plan the UAV trajectory, thus ensuring the freshness of the information with minimal throughput constraints. Routing protocols are essential for high-speed data transmission. To ensure secure and efficient routing for UAV-assisted vehicular ad-hoc networks, the literature [86] uses an ant colony optimization algorithm to improve the routing algorithm of FANET to supplement disconnected FANET links with UAVs, reducing the end-to-end delay and routing overhead. However, the protocol is vulnerable to attacks by malicious UAVs and still requires appropriate security protocols to ensure route security. To improve the energy efficiency when UAVs are used as flying base stations, literature [87] uses heuristic algorithms to determine the location and altitude of UAVs to

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avoid overlapping coverage of multiple UAVs and equalization of coverage and transmit power of a single UAV. However, the network switching problem due to vehicle movement is not taken into account. UAVs as flying base stations can provide video, music, and other content services to vehicles on roadways without communication infrastructure. However, considering the limited storage capacity and battery capacity of the UAV, it is necessary to plan the UAV's trajectory and cache the contents rationally so as to serve as many vehicles as possible with low energy consumption. In [88], the PPO-Clip algorithm is used to control the UAV's trajectory to maximize the energy efficiency of the UAV, i.e., to maintain as many downlinks as possible with the lowest energy consumption. In this case, the UAV can both acquire content from and provide content to the vehicle. However, the scenario assumed in this paper only considers the one-way driving process of a section of road and does not consider the continuity of UAV services, and the scenario assumptions still need further improvement.

3.3.3. Healthcare

In healthcare, UAVs can perform tasks such as human health information collection and medical supply delivery. The authors in [89] propose the use of UAVs to monitor the body area network (BAN) and also consider a specific scenario where a link is established with the driver through a vehicle network to monitor the condition of the human body and prevent accidents. In today's COVID-19 pandemic, UAVs are also used to collect samples and deliver medical supplies, which not only saves human resources but also effectively avoids the risk of being infected [90]. However, UAVs are often involved in the sharing of medical data when providing healthcare services, in which case it is easy for data leakage to occur. Fortunately, blockchain technology brings a solution to the problem of security and privacy of data [91,92]. Blockchain uses cryptographic techniques such as hash functions and public key encryption to protect shared data and can be used to ensure the authenticity of stored information as well as improve the security and transparency of UAVs, helping to overcome many of the problems UAS face such as coordination, security, collision avoidance, privacy, decision-making, and signal interference [93].

3.4. Military

UAVs play a significant role in contemporary warfare and are a vital part of military technology. UAVs can, for instance, create temporary data networks, use sensors to survey the battlefield, locate targets using advanced AI algorithms, and even serve as weapons to carry out military missions [94,95]. Battlefield environments are extremely dangerous and highly dynamic, and UAVs need to constantly adjust their trajectories to the situation to ensure their safety. To achieve fast path planning, a genetic algorithm implemented in parallel on a graphics processing unit was proposed in [96]. The UAV trajectory is represented by points in 3D space, and the GA algorithm generates the trajectory by moving these points. This method minimizes fuel consumption while significantly reducing the path planning time. Another thing to think about in military warfare is how to protect UAVs. During missions, UAVs constantly send encrypted location information to ground-based stations, which can pose a serious threat to UAVs if leaked. Literature [97] uses UAVs to collect encrypted messages sent by enemy UAVs within line of sight and their fuzzy location information, and uses NNs to learn the correspondence between plaintexts and ciphertexts to crack the plaintexts. When the number of opposing UAVs is higher, the amount of data that can be collected is larger, which allows for training a more accurate NN model. Therefore, military UAVs should avoid being deployed in large numbers in small areas.

4. Tasks and Methods in AI-Enabled UAV-Assisted IoT

The IoT application scenarios and specific application instances were thoroughly explained in the previous chapter. In these scenarios, data collection and network service provision can be summed up as the main roles of UAVs. Next, we will explain and

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outline the issues that UAVs will face while executing these tasks, the metrics that must be addressed, and the related AI solutions, taking into consideration relevant literature.

4.1. Data Collection

An important application scenario for UAVs is to collect information from the sensor network and send this information back to the data center for processing. One of the most important things in this process is to plan the UAV path rationally. This is because the data has different requirements for time delay and the UAV has limited energy. In the process of collecting data, the flight path of the UAV needs to be planned reasonably according to the age of information, data collection efficiency, energy consumption, and other requirements. Compared with traditional optimization algorithms, AI algorithms such as group intelligence-based algorithms and reinforcement learning algorithms can effectively cope with the dynamic environment and obtain near-optimal solutions in real time to dynamically plan UAV paths. In the following article, we will summarize the literature on UAV data collection in terms of three metrics: data collection timeliness, data collection efficiency, and energy consumption. Table 3 summarizes the optimization targets, performance metrics, and AI solutions for UAVs performing data collection.

Table 3. Optimization targets, performance metrics, and AI solutions during UAV in performing data collection.

Optimization Target	Performance Metrics	AI Methods	Reference
Path planning	AoI	DQN	[98]
Path planning	AoI and energy	DQN	[99]
Path planning and hover position	AoI and energy	TD3	[100]
Path planning	AoI, energy and packet loss rate	DQN	[101]
Path planning	Delay and energy	GA	[102]
Path planning	AoI	Q-learning	[103]
Path planning and collision avoidance	AoI	Sarsa	[104]
Path planning	Collection time	TD3	[105]
Path planning	Collection time and energy	SADOL and MADOL	[106]
Path planning	Data collected	Dueling DQN	[107]
Path planning	Data acquisition performance	DNN and DQN	[108]
Path planning	Data collocation efficiency and energy	ACO	[109]
Path planning and transmit power allocation	Energy	Sarsa	[110]
Path planning and hover position	Energy	AEM	[111]
Path planning	Energy	Ptr-A*	[112]
Path planning	Energy	ACO	[113]
Path planning	Energy	K-means and GA	[114]
Path planning and collision avoidance	Data collocation efficiency	D3QN	[115]

AoI is a metric that characterizes the freshness of information and can also be used to indicate the timeliness of information transmission. In order to reduce the AoI weighted sum of sensor information collected by the UAV, a DQN-based UAV-assisted data collection algorithm is proposed in the literature [98] to control the flight direction of the UAV and the connected sensors. Also, energy and start-termination point constraints are considered in that literature. A more complex scenario is considered in literature [99], where the UAV has to charge the ground nodes before data collection. The scheduling of information and

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energy transfers is jointly considered in the trajectory optimization process to minimize the average AoI of the system, and a DQN scheme with two ANN networks is proposed to solve the problem. In order to minimize the weighted sum of the average AoI, the propulsion energy of the UAV, and the transmission energy of the IoT device, literature [100] proposes a twin-delayed deep deterministic policy gradient-based UAV trajectory planning algorithm to jointly optimize the UAV's flight, hover position, and data collection bandwidth allocation. Also, the TD3-AUTP algorithm outperforms the DQN and AC algorithms in terms of achievable AoI and energy efficiency. AoI, packet loss rate, and UAV energy consumption are jointly considered in literature [101], and the DQN algorithm is used to find the optimal trajectory. Experimental results demonstrate that this scheme can effectively reduce AoI and packet loss rates compared to the greedy algorithm. The information collected by UAVs during surveillance and remote sensing is often very time-sensitive. Therefore, to ensure that the collected data can be transmitted in a timely manner, a GA-based approach was used in the literature [102] to find the UAV flight path that satisfies the timeliness, energy, storage, and communication constraints. In order to ensure the timeliness of data and avoid data packet expiration or loss, literature [103] considers the AoI and deadline of the data and uses Q-learning to plan the trajectory of the UAV to reduce the expired data packets. Compared to GA, Q-learning performs better in terms of time consumption. Literature [104] also considers the collision avoidance problem during UAV data collection, using a Sarsa-based learning algorithm to minimize the sensor's average AoI under the constraints of UAV energy and collision avoidance. The proposed sarsa-based learning algorithm can approximate the optimal policy when certain conditions are met.

The data collection efficiency of the UAV is determined by the amount of data collected and the data collection time. The greater the amount of data collected per unit time, the higher the data collection efficiency. In order to improve the efficiency of UAV data collection, literature [105] proposes a deep reinforcement learning algorithm based on TD3 to design the trajectory of the UAV under throughput and motion constraints to minimize the data collection time. Similarly, to reduce the data collection time, the literature [106] proposes the single-intelligent-depth option learning (SADOL) algorithm and the multi-intelligent-depth option learning (MADOL) algorithm to plan data collection paths for energy-constrained UAVs for deterministic and indeterministic boundary scenarios, respectively. Considering the limitations of UAV on-board power and flight time, UAV needs to maximize data collection from wireless network devices under the shortest flight path, thus improving data collection efficiency. In the literature [107], a DQN-based algorithm is proposed for finding the optimal trajectory and data collection in a specific coverage area and balancing between data collection, trajectory, and convergence time. Dueling DQL is also used to improve the system's performance and convergence speed. The success rate of data collection is also an important indicator in the process of data collection. To solve the UAV data acquisition problem under dynamic scenarios such as moving nodes, node additions, and deletions, a two-stage deep reinforcement learning framework is proposed in the literature [108] to plan UAV trajectories online, where the first layer uses DNN to model the dynamically changing environment and the second layer uses DQN to plan trajectories online. Experimental results show that this two-stage deep reinforcement learning framework can improve the data acquisition success rate. In addition, literature [115] considers the collision avoidance problem in a data collection scenario with multiple UAVs in a non-cooperative scenario and proposes a dueling double-depth Q-network (D3QN)-based algorithm to learn the decision strategies of typical UAVs without prior knowledge of the environment, which avoids collisions while maximizing the amount of collected data.

The transmission of large amounts of redundant data, too low data collection efficiency, and the unreasonable allocation of UAV transmitting power can cause energy consumption. In order to reduce the energy consumption caused by redundant data transmission, a matrix completion-based sampling points selection joint Intelligent Unmanned Aerial

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Vehicle Trajectory Optimization (SPS-IUTO) scheme was proposed in the literature [109]. The scheme selects sampling points using a matrix-based approach and optimizes the trajectory using an optimized ant colony optimization algorithm. To minimize the total energy consumption of all devices during UAV data collection, literature [110] uses the SARSA algorithm to obtain the UAV trajectory, thus solving the joint problems of UAV trajectory, device association, and transmit power allocation while ensuring that each device should meet a given data rate constraint. For collecting data from massive machine-like communication mMTCs, it is necessary to find the best hovering position and flight strategy for the UAV within the cluster to minimize the UAV's energy consumption. In [111], a novel modeling technique based on the idea of artificial energy map (AEM) is proposed for finding the UAV's hovering position. Firstly, greedy learning clustering (GLC) is used to optimize machine-type communication device clustering and UAV hovering strategies to minimize transmission and hovering energy. Genetic algorithms are then used to find the flight strategy with the lowest energy consumption. Article [112] uses UAVs to access cluster heads in a certain order to solve the data collection problem of clustered wireless sensor networks and proposes a pointer network-A* (Ptr-A*) based algorithm for planning UAV paths, thus reducing the energy consumption of UAVs in the process of data collection. Agricultural monitoring also requires the collection of data from a large number of sensors. Just like [111], the literature [113] first clusters the sensors, where a hierarchical data collection scheme is proposed to improve the node clustering efficiency. The UAV's path is then planned by an ant colony optimization algorithm. The experimental results show that this scheme can collect data efficiently at a low energy cost. Similarly, the literature [114] uses K-means to cluster sensors and then uses GA to plan the UAV trajectory, thus reducing energy consumption.

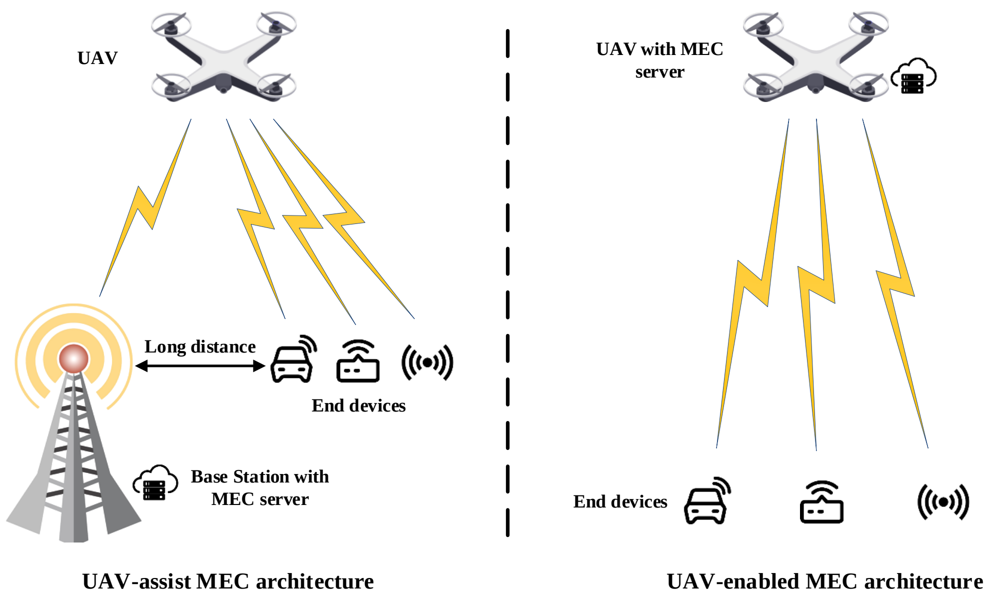

Figure 6. UAV-assisted and enabled MEC architectures.

4.2. Network Service Provision

Thanks to the rapid development of cloud computing and mobile edge computing technologies, UAVs can carry MEC servers or establish connections to MEC servers to provide low-latency and highly reliable computing and processing services to resource-limited devices. UAV-assisted and enabled MEC architecture has been widely discussed and has attracted a lot of research in academia, and the architecture can be seen in Figure 6 [8]. However, considering the limited energy of UAVs, computational offloading, data offloading, trajectory optimization, and resource allocation need to be addressed during

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service provision to improve energy efficiency and service quality. Since both computation offloading and task offloading consume the computational resources of servers, and since there is not much difference between them, they are collectively referred to as "computing offloading" in this paper. AI, especially RL, which is widely used to improve network performance thanks to its ability to make real-time decisions based on the environment, provides a solution to the problems under the dynamic UAV-assisted and enabled MEC architecture to further improve network performance and user service quality of experience. Table 4 summarizes the optimization objectives, performance metrics, and AI methods for UAVs in providing network services.

Table 4. Optimization targets, performance metrics, and AI solutions during UAV in providing network services.

Optimization Target	Performance Metrics	AI Methods	Reference
Computing offloading and resource allocation	Delay and energy	MARL	[116]
Resource allocation	Delay and QoS	MADDPG	[117]
Computing offloading	Delay	DDPG	[118]
Computing offloading and resource allocation	Delay	iTOA	[119]
Computing offloading and path planning	Delay	DQN	[120]
Computing offloading and resource allocation	Energy and delay	AC	[121]
Computing offloading and resource allocation	Energy and delay	SAC	[122]
Computing offloading, resource allocation and power control	Energy	MARL	[123]
Computing offloading and path planning	Energy, throughput and QoS	DDQN	[124]
Computing offloading and path planning	Energy	AC	[125]
Computing offloading and path planning	Delay and convergence	DDPG and DQN	[126]
Computing offloading and resource allocation	Delay and energy	TD3	[127]

Improving the quality of UAV network service is an important issue for UAV to consider when providing network services. The main metrics for evaluating UAV network services are QoS and service delay. The typical practice is to expand the service range of the UAV network, improve the QoS of users, and reduce the service latency of users through UAV trajectory planning, resource allocation, and computation offloading. However, it is still necessary to pay attention to the fairness and throughput of the UAV communication system in the process of optimizing network services to avoid skewing and wasting resources. In [116], UAVs are equipped with some computing resources to act as edge servers and collaborate with the ground base station to process the tasks of the ground devices. And a multi-intelligent reinforcement learning algorithm is proposed for solving the joint

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optimization problem of computational allocation and resource allocation, thus reducing the task response time under the energy constraint of UAVs. The MEC-and UAV-assisted vehicular networks were considered in [117], where UAVs and base stations equipped with MEC servers provide services to ground vehicles. And a MADDPG-based scheme for managing multidimensional resources is proposed to cope with highly dynamic vehicle scenarios with latency-sensitive and computationally intensive applications. This scheme can meet the latency and QoS requirements of vehicles. The literature [118] uses the DDPG algorithm to provide computational offloading decisions for single UAV-assisted multi-user scenarios. Experimental results demonstrate that the DDPG algorithm is easier to converge on and can achieve lower latency compared to the DQN algorithm. In [119], tasks can be executed locally in the UAV or sent via the UAV to the MEC server for execution. An intelligent task offloading algorithm (iTOA) based on the AlpahGo core algorithm, MCTS, and UAV edge computing network is proposed to solve the computational offloading and computational and communication resource allocation problems. The iTOA algorithm improves the latency performance of the system compared to greedy search and game theory-based task offloading methods. When UAVs are used as flying base stations, they can provide flexible service coverage through trajectory planning. A three-tiered edge computing system is used in [120], where sensors in the first tier generate data, UAVs in the second tier carry MEC servers for initial processing of the data, and the operations center in the third tier does the final processing of the data. The combined scheme reduces the data latency by planning the UAV path through DQN and then scheduling the network through Lyapunov optimization.

Energy efficiency is another issue that UAV needs to be concerned about in providing network services. The energy efficiency of UAVs in providing network services includes the energy efficiency of the UAVs and the energy efficiency of users. The energy efficiency of UAVs is positively correlated with their effective service time. We can improve the energy efficiency of UAVs by reducing energy consumption, improving service efficiency, and extending the service time of UAVs through trajectory planning, computational offloading, and power control. For users, launch power is the main source of energy consumption, and UAVs can reduce users' launch power by optimizing trajectories. In [121], a SAG-IoT network architecture is considered in which UAVs carry MEC servers, satellites are connected to cloud servers through a backbone network, and tasks generated by IoT devices can be executed locally or offloaded to UAVs and satellites. An actor-critic based reinforcement learning algorithm is proposed to solve the computational offloading problem of SAG-IoT. The UAV and MEC server resource allocation and task scheduling problem is formulated as a mixed integer programming problem, and a heuristic algorithm is proposed to solve it. Compared with random and greedy algorithms, this scheme can achieve both low latency and low energy consumption. The UAV-assisted MEC architecture needs to consider the communication link from the UAV to the MEC server and requires additional consideration for the allocation of communication resources. In [122], the UAV is used to help the user complete computational tasks as well as to establish stable wireless communication between the user and the MEC server. That is, the UAV and the MEC server collaborate to process the tasks provided by the user. A soft-actor-critic (SAC) algorithm is proposed for determining dynamically superior computational offloading and resource allocation policies in terms of latency, energy consumption, and task discards. The literature [123] considers the economic issues in UAV-assisted MEC systems and proposes a multi-intelligent reinforcement learning algorithm to jointly power control and resource allocation and make offloading decisions for users. The system energy consumption is reduced while the system performance is guaranteed, thus improving the UAV revenue. The literature [124] considers a scenario where a single UAV serves mobile ground users and is equipped with an MEC server. A DDQN-based algorithm is proposed to optimize the UAV trajectory to maximize system throughput with guaranteed UAV energy and user QoS constraints. And the performance of DDQN is better than DQN. Similar to [124], the literature [125] considers the use of a single UAV equipped with a MEC server to serve ground users and

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uses an actor-critic-based algorithm for controlling trajectories. The difference is that the goal of the literature [125] is to minimize the energy consumption of all users.

In addition, the issues of algorithm convergence and learning efficiency in large scenarios are also to be considered. A single UAV has limited service capability to meet the needs of users in large-scale scenarios. But enabling multiple UAVs leads to an exponential growth of the system state space and actions, also called dimensional disaster. A hierarchical trajectory optimization and offload optimization (HT3O) algorithm was designed in the literature [126] to reduce the complexity of the problem and improve the learning efficiency through alternate optimization, where the DDPG algorithm and DQN algorithm were used for trajectory and offload optimization separately. The scheme is capable of fast convergence and is effective in reducing the average task latency compared to ordinary reinforcement learning algorithms. In [127], multiple UAVs are used to assist in the computation as well as to offload the tasks further to the edge cloud. To solve the dimensionality problem, a multi-intelligent TD3 algorithm is used to jointly optimize the UAV trajectory, computational offloading, and communication resource allocation in dynamic MEC environments, thus reducing latency and energy consumption.

5. Open Issue

AI not only enhances UAV network performance but also brings intelligence to UAVs and has decision-making capabilities, which can give UAVs the autonomy to respond flexibly to real-time changes in the environment. While there is a large body of literature on the use of AI to enhance UAV services, there are still some issues to consider when applying AI to UAVs and UAV-assisted IoT.

5.1. AI Training and Convergence Problems

The application of AI algorithms, especially RL algorithms in communication networks, has been heavily researched but requires a large amount of data for training to achieve good results. Unfortunately, training data is often difficult to obtain. Moreover, these collected data may also suffer from redundancy, label errors, and class imbalance, which severely affect the AI training results [13]. Data augmentation can generate new data based on existing data, can avoid the problem of overfitting, and is an important way to solve the problems of lack of training data and algorithm convergence. Federated Learning (FL) executes ML algorithms in a decentralized manner and updates model parameters through the interaction of local and global models. The distributed joint training method of FL can solve the problem of imbalanced training data. For example, a UAV with less training data can update the local model through the training results of other UAVs to ensure the effectiveness of training.

In addition, AI algorithms do not easily converge in the presence of large environments and action spaces. Alternating iterative learning methods can be used to reduce the problem complexity and thus solve the convergence problem of AI algorithms in large-scale scenarios [126]. However, related research still needs to be improved to flexibly respond to various situations. The emerging graph neural networks (GNN) in recent years have had good results in dealing with large-scale scenarios. GNNs use graph structures that greatly improve data analysis and reduce the number of network parameters and thus computational complexity by using a message passing mechanism similar to that of distributed optimization algorithms [128]. In literature [129], a GNN-based method is proposed to solve the joint optimization problem of UAV location and relay path selection under large-scale networks, which is able to achieve the same performance in small-scale network scenarios with twice the time complexity of violent search. Moreover, the method is scalable to adapt to dynamic environments and still converges quickly to the best performance in large-scale scenarios. In the future, GNN will be an important way to solve the convergence problem of AI algorithms in large-scale scenarios.

5.2. Resource and Energy Constrained Issues for UAV

Since UAVs have limited energy and will consume energy during flight, the issue of energy conservation becomes more important when applying AI and MEC servers, which are energy-intensive algorithms and devices, to UAVs. In addition to using algorithms to perform other energy-saving operations, such as trajectory planning for UAVs, to improve the energy efficiency of UAVs. For example, in the literature [110], energy consumption was reduced by optimizing the UAV trajectory and transmit power to improve the UAV data collection efficiency. In [121], resource allocation and task scheduling were jointly optimized to reduce energy consumption. We can also investigate lightweight AI algorithms, such as GNN or distributed learning algorithms that run on resource-constrained devices to provide solutions for resource-constrained networks [12]. The literature [130] also proposes a dynamic NN that uses a knowledge base to select the network width, i.e., dynamically adjusts the model complexity according to the service demand, thus achieving a reasonable match between demand, resources, and performance. Some AI algorithms can also use DyNN to dynamically adjust the network width according to task demand, thus achieving energy savings. In addition, hardware performance improvements and software and hardware adaptations are important ways to allow AI algorithms to run on UAVs with limited resources and energy.

5.3. Security and Privacy Issues for AI and UAV

UAVs may be attacked by malicious devices during flight, such as hijacking and sabotage of UAVs; jamming UAV communications by faking identities; and eavesdropping on UAV communications. This not only affects the security of UAV communication but also may interfere with UAV flight, leading to UAV collisions. In addition to the communication security issues regarding UAVs that have been discussed in Chapter 2, data security and privacy issues are also important when training AI models. When training AI models, data needs to be collected from various nodes, and it is very easy for data leakage to occur in this process. FL builds global models by exchanging model parameters, which reduces the transmission of network data traffic and protects users' data privacy and security. FL has been used for UAV trajectory control, and network security, and is a good method to protect the safety of AI training [131,132]. However, due to the existence of model data transfer during training, FL is still subject to attacks, e.g., by injecting anomalous data and thus affecting the training process of the model. Moreover, for FL, this attack also penetrates the entire network through the training process. The integration of blockchain technology with FL is a solution to improving the security of FL. In [133], the authors introduce a blockchain-based FL architecture for UAVs that ensures privacy protection in FL. However, the convergence problem of FL is not guaranteed, and the data differences of different nodes and model update speed differences will have an impact on the convergence speed of FL. Related issues still need further research in the future [6].

6. Conclusion

UAV brings communication services to anywhere there is a need with very low cost and very fast response, leading to UAV-assisted IoT, a new development direction of IoT, and providing communication technology support for the development of IoT. Together with the support of MEC's powerful computing and storage capabilities and AI's powerful processing and analysis capabilities, UAV becomes more intelligent, autonomous, and able to provide more services, injecting new energy into the development of UAV-assisted IoT. This paper introduces UAV communication technology, IoT technology, and AI technology in detail, analyzes the potential application and development direction of using AI to empower UAV-assisted IoT, and comprehensively reviews UAV communication technology, networking technology, collision avoidance technology, and application scenarios of UAV-assisted IoT, and summarizes the existing problems and corresponding AI solutions. Finally, we summarize the problems and analyze possible solutions when applying AI to UAV and UAV-assisted IoT.

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