Mobile Edge Computing and Machine Learning in The Internet of Unmanned Aerial Vehicles: A Survey

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Unmanned Aerial Vehicles (UAVs) play an important role in the **Internet of Things (IoT)**, and form the paradigm of the Internet of UAVs, due to their characteristics of flexibility, mobility and low costs. However, resource constraints such as dynamic wireless channels, limited battery capacities and computation resources of UAVs make traditional methods inefficient in the Internet of UAVs. The thriving of **Mobile Edge Computing (MEC)** and **Machine Learning (ML)** is of great significance, and is promising for real-time resource allocation, trajectory design and intelligent decision making. This survey provides a comprehensive review of key technologies, applications, solutions and challenges based on the integration of MEC and ML in the Internet of UAVs. First, key technologies of MEC and ML are presented. Then, their integration and major issues in the Internet of UAVs are presented. Furthermore, the applications of MEC and ML in the Internet of UAVs under urban, industrial and emergency scenarios are discussed. After that, this survey summarizes the current solutions for MEC and ML in the Internet of UAVs based on the considered issues. Finally, some open problems and challenges are discussed.

CCS Concepts: • **Networks** → **Mobile networks**; • **General and reference** → **Surveys and overviews**; • **Computing methodologies** → **Machine learning**.

Additional Key Words and Phrases: The Internet of unmanned aerial vehicles, mobile edge computing, machine learning, computation offloading, intelligent decision making

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1 INTRODUCTION

With the advent of the **Six-Generation (6G)** era, the **Internet of Things (IoT)** is booming [87], and various services and applications are emerging, including information recognition, driverlessness, and navigation [116]. The IoT can integrate multiple application areas including transportation, health, agriculture and medical care, and complete the automated interoperability of information inside. This makes the amount of data processed by the IoT increasingly incremental, and causes practical applications be more and more complex [74]. It also brings about many issues, such as insufficient wireless channels due to the steep increase in the number of IoT devices, and ultra-low latency requirements of IoT applications [75].

The **Unmanned Aerial Vehicle (UAV)**, as a tool that has gradually developed and matured in recent years, is active in various fields with its, flexibility and relatively low costs [62]. It can not only provide a non-contact solution to the COVID-19 epidemic in recent years [75], but also become a tool to solve problems in many fields, such as post-disaster reconstruction, traffic condition detection, and target tracking [109]. The advantages enable UAVs to act as data collectors and **Edge Servers (ESs)** in IoT systems [73], providing storage and computation services for some special or urgent scenarios [128]. Therefore, UAVs can be integrated with IoT devices to extend services from the ground into the air, forming the Internet of UAVs.

Mobile Edge Computing (MEC) is one of the most widely studied technologies in recent years [110], and has an excellent performance in terms of resource allocation efficiency and latency [111]. However, it is difficult to provide the infrastructure for MEC in remote and mountainous areas. Moreover, under an emergency scenario like a disaster, the deployment of fixed computing devices is too costly and not easy for installation [134]. Fortunately, UAVs can be utilized in areas with poor infrastructure to provide communication and computing services for users.

Meanwhile, integrating **Machine Learning (ML)** with the Internet of UAVs is promising to realize intelligent decision making and perception capabilities [6], which are efficient in solve complex problems, such as UAV trajectory optimization [119]. However, due to the time-varying channel environment in the Internet of UAVs, it is difficult for computation as well as communication resource allocation and task scheduling in the Internet of UAVs merely relying on traditional optimization methods, especially with fast fading channels [31]. In addition, dynamic task arrivals and heterogeneous devices in the Internet of UAVs complicate the offloading decision [36]. What's more, the limited computation resource of UAVs makes ML lack of sufficient resources for training or inference. Fortunately, the integration of MEC and ML can complement each other, and two network architectures can be formed, i.e., ML-enabled MEC and MEC-enabled ML. The former enables reasonable offloading decision making for dynamically generated tasks, and the latter allows ML to be executed on devices with insufficient computation resources.

1.1 Prior Related Surveys

In recent years, a number of surveys summarize the state-of-the-art of the Internet of UAVs. Some studies focus on applications in the Internet of UAVs. For example, authors in [25] summarize the civil applications of the Internet of UAVs, analyze their characteristics and metrics from the perspective of communication and networking, and present the feasibility of integrating existing technologies with the Internet of UAVs. Authors in [68] study advantages and applications of UAVs in wireless communication networks, and provide some key challenges, such as UAV deployment and wireless channel modeling. Authors in [95] study UAV applications in cyber-physical systems, and discuss challenges and corresponding solutions.

In addition, there are some studies focusing on technologies used in the Internet of UAVs. Authors in [16] summarize the types of UAVs and challenges in cellular UAV networks, discuss the interference problem, and provide a physical security model for UAV-assisted cellular networks. A classification of issues in the Internet of UAVs is given in [22], and routing protocols developed to accommodate high mobility, flexibility, link variation, and power limitations are discussed. Authors in [100] analyze problems and challenges arising from the integration of the Internet of UAVs and the commerce, and propose a set of relevant regulations at social and commercial levels. Authors in [67] study how to leverage game theory to realize the coordinated control of UAVs in wireless networks, and present their own insights on these solutions. Besides, authors in [28] conduct an extensive study on ML applied to the Internet of UAVs from trajectory control and resource allocation perspectives.

Although the above studies have surveyed the Internet of UAVs from different aspects, ***the integration of MEC and ML in the Internet of UAVs and its applications have not been comprehensively studied.***

1.2 Contributions

In this survey, we summarize technologies, applications, solutions and challenges of ML and MEC in the Internet of UAVs. According to the mutual support of MEC and ML in the Internet of UAVs, the integration of MEC and ML can be divided into ML-enabled MEC and MEC-enabled ML. The former supports MEC for intelligent decision making, and the latter supports inference and training offloading of ML. Specifically, the main contributions of this survey are as follows:

- We first present technologies of MEC and ML in the Internet of UAVs and specify their integration. Then, we summarize the key issues of MEC and ML in the Internet of UAVs. We conduct a comprehensive overview of related hot topics through the analysis of key issues.
- We present applications of the Internet of UAVs with the integration of MEC and ML in urban, industrial and emergency scenarios and provide a detailed introduction for each kind of applications. It demonstrates the important role in industrial areas and that of people's daily life provided by the Internet of UAVs, and it is promising to extend the corresponding applications, such as city surveillance and IoT data analysis.
- We summarize and categorize solutions for key issues of MEC and ML in the Internet of UAVs and provide corresponding lessons. In addition, we compare state-of-the-art solutions to classify different research focuses and applied technologies. In addition, we provide lessons to summarize the progress and shortcomings of the current studies.
- Finally, we discuss research challenges and provide several open issues for the Internet of UAVs based on ML and MEC, providing an overview of future research directions in the current state-of-art.

1.3 Structure

This survey is organized as follows: In Section 2, we focus on the technologies of MEC and ML in the Internet of UAVs, and introduce the architecture and issues of the integration of MEC and ML; In Section 3, we discuss applications of the Internet of UAVs with the integration of MEC and ML in different scenarios; In Section 4, we introduce the solutions in the Internet of UAVs with the integration of MEC and ML; Some research challenges and open issues are provided in Section 5; Finally, this article is summarized in Section 6.

2 TECHNOLOGIES FOR MEC AND ML IN THE INTERNET OF UAVS

In this section, we present key technologies and the integration of MEC and ML in the Internet of UAVs. First, this section details MEC in the Internet of UAVs. Second, brief introduction and categories of ML in the Internet of UAVs are discussed, and lessons of MEC and ML applied in the Internet of UAVs are summarized. Finally, we discuss the integration of MEC and ML in the Internet of UAVs, and provide corresponding architectures and research issues.

2.1 MEC in The Internet of UAVs

As shown in Fig. 1, with the development of IoT, ESs can be utilized to provide computation resources for on-ground users to meet their computation demands [72]. To realize MEC in the Internet of UAVs, four key

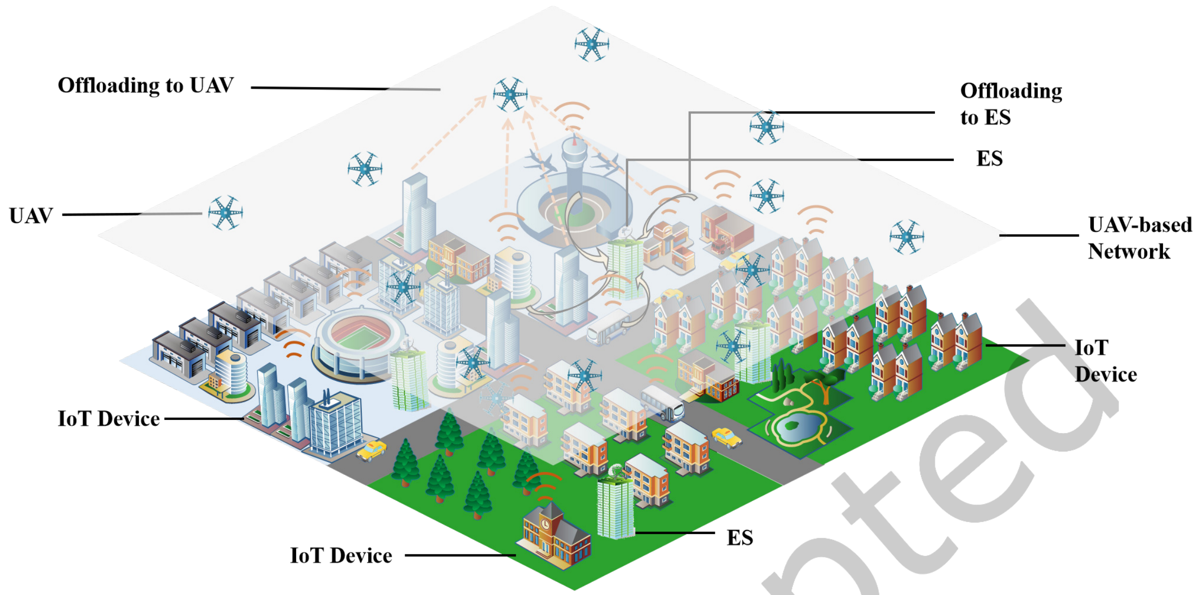

Fig. 1. Computation offloading architecture in the Internet of UAVs.

aspects need to be considered: a) computation task offloading; b) UAVs acting as ESs; c) collaborative scheduling among UAVs; and d) channel enhancement. In the following, we describe them in detail.

2.1.1 Computation Task Offloading. Generally, computation task offloading can be divided into complete offloading and partial offloading. Complete offloading, also known as binary offloading, means that the entire computation task is fully handled by ESs [64], and can be used for tasks that are simple or can not be partitioned [65]. Partial offloading means that some parts of the task are selected for offloading, and the remaining parts are processed locally [73]. UAVs are deployed in heterogeneous IoTs, and tasks have different accuracy requirements [5]. Binary offloading is suitable for tasks with high accuracy requirements, such as channel estimation, while partial offloading is suitable for tasks with high computation demands and relatively low accuracy requirements, such as image processing [135]. Generally, partial offloading consists of roughly six steps. First, it is necessary to find nearby available ESs. Then, the task is partitioned. After that, IoT devices interact with UAVs to estimate whether the completion latency meets the requirement. If so, the task is transmitted [138]. The next step is task processing by ESs. Finally, results are returned to the device [64].

2.1.2 UAVs Acting As ESs. In the Internet of UAVs, UAVs are usually leveraged as ESs to provide computation services to terminal devices. However, UAVs are small in size and have limited computation capacity [43]. Spectrum and channel resources for UAVs are limited [44], causing severe interference between UAVs and users. In addition, after the offloading decision is made, it is necessary to consider how many computation resources are allocated to handle the task [90]. This makes the allocation of computation and communication resources rather complex when UAVs act as ESs. Furthermore, we need to consider the dynamic number of users and the amount of tasks in the Internet of UAVs when solving the computation and communication resource allocation problem, since load balance needs to be considered among UAVs [120].

Computation resource allocation can be classified into the case with single and multiple edge nodes. When a single edge node serves multiple users, we need to consider whether its own computation resources can meet the

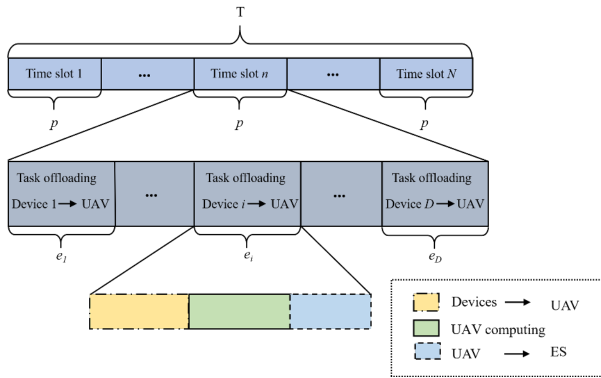

Fig. 2. Time slot division in the TDMA-based scheme [138].

requirements of users, how to improve service efficiency, and how to minimize the total task completion delay. When multiple nodes serve multiple users, we need to consider how to integrate these computation resources to reduce the task completion latency and minimize energy consumption [64]. In addition, we need to balance energy consumption and latency to avoid the performance collapse of other aspects caused by pursuing one aspect too much [85]. What's more, the flexibility of UAVs allows them to utilize idle resources to improve computation efficiency, and thus UAVs can serve as both relays and ESs.

The allocation of communication resource focuses on how to improve spectrum utilization and reduce channel interference. Generally, **Time Division Multiple Access (TDMA)** is adopted, as shown in Fig. 2. Considering UAVs as ESs, a time block with length T is partitioned into N time slots, each of which with length $p = T/N$. Each time slot is then divided into sub-slots with duration e_i, and these sub-slots are allocated to IoT devices for communication [120]. Furthermore, considering UAVs as both ESs and relay nodes, further division with three sub-sub-slots is performed on the sub-slot. In the first one, tasks from IoT devices are offloaded to UAVs. In the second one, computation tasks are processed by UAVs. Tasks are forwarded to ESs for processing by UAVs as relay nodes in the third sub-sub-slot [138]. In addition, technologies such as **Non-Orthogonal Multiple Access (NOMA)** and **Orthogonal Frequency Division Multiple Access (OFDMA)** can also be applied to the Internet of UAVs to improve spectrum utilization [46]. Compared with TDMA, NOMA enables multiple users to share a common channel, despite costly anti-interference treatment at the receiver or transmitter [120]. OFDMA achieves multiple access by assigning orthogonal subcarriers to different users [138].

2.1.3 Collaborative Scheduling among UAVs. The service capacity of a single UAV is limited to meet the computation demand of a large number of IoT users in the Internet of UAVs. When multiple UAVs provide services simultaneously for the IoT, without reasonable trajectory design and resource scheduling [126], some UAVs may be overloaded, while others are even in the idle state. This dramatically affects the performance of the Internet of UAVs and wastes the valuable resources of UAVs. It is also necessary to consider the security of multiple UAVs to avoid collisions among UAVs while performing computation offloading [41]. In the collaborative scheduling of multiple UAVs, researchers focus on how to coordinate the locations of multiple UAVs to maximize the service coverage, and how to improve resource utilization efficiency and reduce the total energy consumption of the system. Generally, IoT nodes are unevenly distributed, which means that the trajectory design of UAVs can have a great impact on **Quality of Service (QoS)** [126]. In addition, the trajectory overlap among UAVs, i.e., trajectory coupling, needs to be considered [140].

2.1.4 Channel Enhancement. In the Internet of UAVs, UAVs perform computation offloading in dynamic wireless communication networks, where the network environment and channel conditions are constantly changing. It severely affects the offloading efficiency and delay. Therefore, channel enhancement is needed. In traditional UAV-enabled MEC networks, the **Line of Sight (LoS)** channel between the UAV and the user is generally established by changing the position of the UAV to improve channel conditions. In this process, it is necessary to pay attention to UAV propulsion energy consumption and the waiting time of users to avoid the ignorance of the lifetime of UAVs and the network QoS. In addition, **Intelligent Reflecting Surface (IRS)** can be deployed on the surface of buildings to enhance UAV communications. Specifically shown in Subsection 2.3.3.

Lesson 1: The rise of MEC technology is extremely important for UAVs, which can make use of idle computation resources at the network edge. This enables UAVs as ESs to serve IoT devices, and meet computation requirements of some special scenarios. In summary, UAV-enabled MEC systems have three advantages:

Real-time: The flexible and easy-to-deploy features make UAVs possible to provide timely data processing services for IoT devices [2]. UAVs' real-time provision of computation services increases the applicability of MEC.

Distributed: Unlike the traditional BS deployment, UAV deployment is relatively much more flexible. In other words, it can be distributed to achieve offloading scheduling [75], which can not only reduce the system cost, but also enhance the system stability.

Mobility: UAVs can move around during the execution of computation offloading, so the trajectories of UAVs need to be optimized [120] to improve resource utilization efficiency.

Although MEC brings many benefits to UAVs, it also causes some problems accordingly. For example, the energy limitation of UAVs restricts the lifetime of UAVs and requires particular attention in UAV-enabled MEC systems. In addition, UAVs acting as ESs need to communicate with a large number of IoT devices. The spectrum resources are insufficient, and resource allocation techniques need to be adopted to improve spectrum utilization efficiency. Moreover, channel conditions of UAVs are dynamic during flight, which affects communication quality.

2.2 ML in The Internet of UAVs

In this section, we provide a brief introduction of ML in the Internet of UAVs, classify and discuss learning algorithms applied in the Internet of UAVs.

2.2.1 Brief Introduction of ML in The Internet of UAVs. The volume of data in the Internet of UAVs is too large and difficult for traditional methods to process [28]. ML is widely used in the Internet of UAVs to handle high dimensional data. It can be mainly leveraged for power and energy allocation, communication resource allocation, flight control, target identification and monitoring [26], which are described as follows:

Power and Energy Allocation: Due to the high mobility and limited battery capacity of UAVs, power and energy allocation is an important issue. It requires global information of UAVs, such as channel state, but it is difficult to obtain them completely in a dynamic UAV network actually. Power and energy allocation strategies can be obtained in the ML-enabled MEC network through the interaction with the dynamic environment to improve energy efficiency.

Communication Resource Allocation: The spectrum resource is scarce and the changes of UAV locations affect the channel environment. ML can regulate the communication resource allocation strategy according to the changes of the channel environment, UAV location and the number of users to optimize system performance [78].

Flight Control: UAVs have complex flying environments and may fly in built-up cities, forest, hills, etc. ML can help UAVs intelligently adjust their altitudes, directions and flight speeds to ensure the safety of UAVs.

Target Identification: The image data acquired by UAVs are vulnerable to the environment, the flight pose and scale transformation, and ML is able to process these data efficiently, making it possible to use UAVs for target recognition.

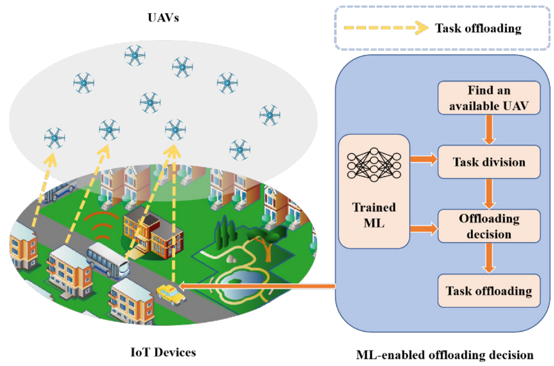

Fig. 3. ML-enabled MEC architecture.

Region Surveillance: ML also enables UAVs to have the capability of urban and environmental surveillance, such as the surveillance of forest fires, and the monitoring of urban road congestion. Specifically, ML can process the data collected by UAVs and extract features to obtain timely state information of the monitored environment.

2.2.2 Algorithms of ML in The Internet of UAVs. Currently, ML applied in the Internet of UAVs mainly includes three categories: **Deep Learning (DL)**, **Reinforcement Learning (RL)** and **Deep Reinforcement Learning (DRL)**.

DL: DL has great advantages in processing high-dimensional data. The main algorithm used in the Internet of UAVs is **Deep Neural Network (DNN)**, which can be leveraged for feature processing of high-dimensional data [129].

RL: Decision making is required in many application scenarios of UAVs, e.g., UAVs need to make flight decisions when performing target tracking tasks. RL enables UAVs to interact with the environment to obtain suitable decisions. The main algorithm applied in the Internet of UAVs is Q-learning. It enables UAVs to acquire suitable policies in a dynamic environment without relying on prior knowledge.

DRL: In the Internet of UAVs, UAVs not only need to process data with high-dimensional characteristics, but also need to make decisions based on these data. DRL is an integration of DL and RL, which has the advantages of the both. The main algorithms applied in the Internet of UAVs include actor-critic, **Deep Q Network (DQN)**, **Deep Deterministic Policy Gradient (DDPG)**, **Multi-Agent Deep Reinforcement Learning (MADRL)** and **Twin Delayed Deep Deterministic Policy Gradient (TD3)**. Among them, actor-critic can solve the continuous flight decision problem in the Internet of UAVs. DQN can be used to solve discrete decision problems for UAVs. DDPG is applicable to continuous action decision problems of UAVs. For the scenarios with multiple UAVs, MADRL can be used to solve the collaboration and game problem among UAVs. In addition, TD3 is applicable to the high-dimensional continuous action space in the Internet of UAVs, and it has high stability.

Lesson 2: The employment of ML in the Internet of UAVs can bring many benefits, mainly in terms of intelligent decision making. ML can enable UAVs to interact with environments for resource allocation and flight decision making in dynamic environments [28]. In addition, ML can also solve mathematical optimization problems that are difficult to solve by traditional convex optimization methods.

However, UAVs are with limited energy and computation resources, and ML training requires a large amount of computation resources. Merely using computation resources of the UAV may significantly degrade the performance of ML.

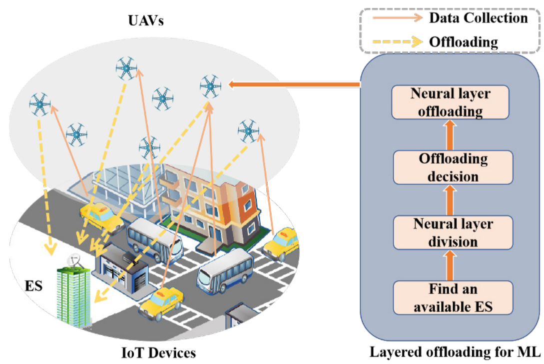

Fig. 4. MEC-enabled ML architecture [124].

2.3 The Integration of MEC and ML in The Internet of UAVs

MEC needs intelligent decisions to adapt to the dynamic environment, and ML needs computation resources to train the learning model. Fortunately, ML can enable MEC to make intelligent offloading decisions in the dynamic environment, while MEC can enable ML to offload inference tasks to ESs by satisfying the demand of computation resources. This subsection introduces two architectures for integrating MEC and ML in the Internet of UAVs, and summarizes the issues need to be considered.

2.3.1 ML-enabled MEC Architectures. Tasks generated by mobile applications are generally time-varying and uncertain. Using only binary offloading makes the system inefficient, while using only partial offloading cannot handle the case of non-separable tasks. This requires dynamic offloading decisions, i.e., whether to split the task and which part of the task needs to be offloaded after splitting. In addition, the practical application scenarios of MEC in the Internet of UAVs have high-dimensional features, which complicate the task offloading decision. Using ML-enabled MEC for offloading can largely improve the offloading efficiency of ESs compared to both binary offloading and ML-free partial offloading. As shown in Fig. 3, IoT devices have tasks to offload, and UAVs act as ESs to provide computation services for IoT devices. First, the nearest idle UAV to the IoT device is searched for, and here the UAV is the ES that provides computation services. Then, whether the task can be segmented and how to segment it are determined by ML. The offloading decision is made for the partitioned tasks, including which part should be offloaded to the UAV for processing and which part should be processed locally.

In this architecture, we need to consider which ML to choose for optimizing the decision process of MEC. Different kinds of ML have distinct advantages and limitations. For example, RL can get into dimensional disasters when solving high-dimensional problems. When choosing ML methods, we also need to model the system in conjunction with the characteristics of the Internet of UAVs, to reduce system latency and energy consumption [90].

2.3.2 MEC-enabled ML Architectures. ML extends applications of the Internet of UAVs with its environment interaction capability, such as UAV target tracking. However, ML itself requires a large amount of computation resources, which makes the scarce computation resources in wireless networks more insufficient. Therefore, the inference tasks of ML can be offloaded, and processed by the deployed ES or idle UAVs. As shown in Fig. 4, the MEC-enabled ML architecture includes UAVs, IoT devices and ESs. Currently, ML offloading focuses on DNN offloading due to its significant role in computer vision for high computation demands, and can be categorized into static partition offloading and dynamic partition offloading. The former one divides layers with the same input, while the latter one is based on the contextual information of the environment and characteristics of

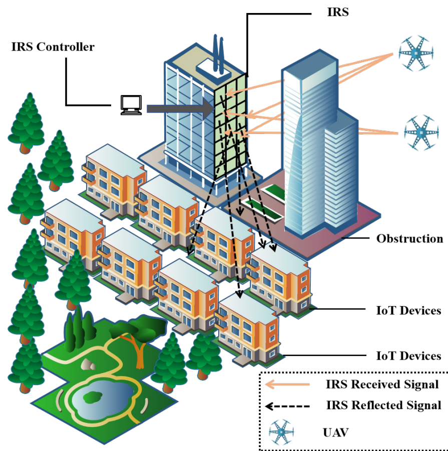

Fig. 5. IRS-enabled UAV communications.

DNN layers. After partitioning, offloading decisions are made for these partitions by considering offloading costs and computation requirements. Integrating MEC with ML is promising to enable IoT devices with limited computation resources to perform ML tasks.

2.3.3 Key Issues. The issues of MEC and ML integration in the Internet of UAVs mainly include:

Dynamic Environment: The mobility of the UAV and users makes the channel environment constantly change, which greatly affects the transmission efficiency. In addition, the demand and density of users are random [112], further increasing the dynamic environment of UAV-enabled MEC. The changing environment makes traditional methods inefficient in solving the problems of UAV-enabled MEC systems. ML can assist UAV-enabled MEC systems to be adaptive to the dynamic environment for intelligent offloading and real-time resource scheduling decisions. Therefore, how to design ML-based methods to solve UAV-enabled MEC systems is an important issue.

Resource Limitations: The computation resource of UAVs is limited, and the service capacity of a single UAV fails to meet the increasing demands of IoTs. Therefore, MEC systems with multiple UAVs are mainly considered at present. In addition, the use of ground ESs can further increase the computation offloading capability of the system. However, the computation offloading also intensifies the energy consumption of UAVs, further reducing the lifetime of UAVs. For the energy limitation problem, some studies focus on the use of energy harvesting to supplement the energy of UAVs timely. In addition, the scarce spectrum resource of UAVs limits the transmission rate and number of users served by UAVs. The use of communication technologies, such as NOMA, is promising to solve this problem.

NLoS Transmission: As shown in Fig. 5, **Non-LoS (NLoS)** scenarios are often encountered during the flight of UAVs, which can degrade the quality of wireless communications [37]. IRS can be used in the Internet of UAVs to improve the quality of communications [139]. IRS consists of a central control element, and a large number of passive reflection units, each of which can be controlled by the central control element to adjust the amplitude, the phase, and the polarization angle of the incident signal [59]. The gain of IRS includes virtual array gain and reflection-assisted beamforming gain. The former one is obtained by combining the direct reflection signal and the IRS reflection signal. The latter one is achieved by controlling the element phase shift by the IRS controller [1]. IRS has the advantages of easy control and low costs, which can make the wireless communication environment suitable to meet communication requirements of the Internet of UAVs [139]. In addition, IRS can be deployed on the external walls of urban high-rise buildings without imposing additional burden on UAVs.

Overloaded UAVs: Owing to the heterogeneity of IoT terminal users, different tasks are generated from user side, leading to the overload of some UAVs. Therefore, we need to consider horizontal offloading of UAVs, i.e., tasks are offloaded between UAVs. In addition, since the channel environment is variable between users and UAVs, to improve system throughput, UAVs will select the users with better channel conditions. This drastically reduces the QoS of some users, and the fairness in the MEC network needs to be guaranteed.

Conflict of Optimization Metrics: There are many optimization metrics in the UAV-enabled MEC systems, such as latency, energy consumption, and throughput. However, the optimization of different metrics may be conflicting, such as latency and energy consumption, i.e., the decrease of latency may cause the increase of energy consumption. Therefore, in the design of UAV-enabled MEC systems, multiple optimization metrics need to be jointly considered to prevent the collapse of a certain index, making the multi-objective optimization problem rather complex.

Threat of Eavesdropping: The UAV-enabled MEC network is vulnerable to the threat of eavesdropping due to the exposed environment and the wireless channel. Although the research on the secure communication of single UAV has been well discussed, the offloading security of multiple UAVs is more complex, and it is necessary to consider not only the security between UAVs and users, but also the communication security between UAVs. In addition, since UAVs may belong to different service providers, user privacy leakage from information transmission between UAVs needs to be considered.

Limitations of ML Inference: Although ML can partially solve the dynamic environment problem in the Internet of UAVs, the inference of ML requires a large amount of computation resources, while UAVs have limited resources and limited storage capacity. Furthermore, the use of ML can intensify the energy consumption of UAVs and shorten their service time. The current research is mainly about offloading the inference tasks of ML deployed on UAVs to ESs to meet computation requirements.

3 APPLICATIONS OF MEC AND ML IN THE INTERNET OF UAVS

This section introduces the applications of the Internet of UAVs with the integration of MEC and ML in three main scenarios, including urban, industrial and emergency scenarios, to demonstrate the important roles of UAVs in the development of IoT.

3.1 Urban Scenarios

With the rapid development of smart cities, emerging applications are gradually increasing in demand. UAVs can be integrated with MEC and ML to provide various services for intelligent transportation, urban surveillance and IoT data analysis. In the following, we will introduce applications in these areas in detail.

3.1.1 Intelligent Transportation. In recent years, traffic congestion and traffic accidents have greatly disturbed people's life, leading to extensive research on intelligent transportation [80]. UAVs are capable of collecting the real-time information of road conditions and providing timely feedback, greatly reducing the response time of traffic accidents. Authors in [23] use UAVs to collect information about vehicles in intelligent traffic systems, which greatly improves the freshness of information. Authors in [45] improve the fairness of data collected by UAVs at traffic nodes through controlling their flight speeds. In addition, there is a large amount of data interaction between vehicles in the Internet of vehicles [82], and UAVs can provide edge computing services for them. Furthermore, authors in [84] use UAVs to serve as ESs to provide latency-sensitive computation services for vehicles, and utilize ML to manage the allocation of computation resources. Authors in [104] leverage ML to coordinate the behaviors of multiple UAVs to provide computation offloading services for ground vehicles, improving the data processing capability of the Internet of vehicles.

3.1.2 *Urban Surveillance.*
UAVs are promising to facilitate real-time monitoring of specific areas, and infrastructure as well as public services can be enhanced based on the collected data to enhance the lived experience of citizens. Authors in [30] consider deploying UAVs to monitor urban safety. In [42], authors use legitimate UAVs to monitor suspicious UAVs, and employ legitimate UAVs to block their receivers to improve eavesdropping rate of legitimate UAVs on suspicious UAVs. UAVs can also monitor crowds in cities to provide timely response to perform situational awareness. Authors in [29] leverage UAV swarm to monitor pedestrians and vehicles in a certain area and shorten the distance between UAVs and targets in a controllable range to provide high-quality monitoring. In addition, authors in [117] use ML-assisted UAVs to track dynamic position of targets.

3.1.3 *IoT Data Analysis.*
The volume of IoT data is increasing gradually, but users at urban locations are facing the shortage of computation resources. Deploying a large number of ESs in the areas with unpredictable spikes in computing demand is not cost-effective. UAVs can relieve the shortage of computation resources in IoT. Authors in [21] use a single UAV as an ES to provide computation services for mobile devices, processing tasks that require high computation and low latency. Authors in [93] use multiple UAVs to provide computation services in IoT, and leverage ML to coordinate the behaviors of multiple UAVs to improve offloading efficiency. Moreover, UAVs can collect data from sensors for processing and promptly transmit results to remote devices. Authors in [133] consider a common data collection scenario for UAVs, where the processed data is delivered to nearby ESs.

3.2 Industrial Scenarios

UAVs can be also used in industrial scenarios to improve plant efficiency and security. With the development of industry, factories are growing in size, bringing management and security issues [77]. This subsection introduces the great potential of UAVs in industrial scenarios in terms of industrial information management and factory security.

3.2.1 *Industrial Information Management.*
The amount of information in the industrial area is large and costly for collection and management. UAVs can perform tasks such as inventorying warehouse, which greatly reduces costs and improves efficiency of inventory. Authors in [51] propose to equip UAVs with radio frequency identification readers to count and manage finished goods and raw materials on **Three-Dimensional (3D)** shelves in tobacco warehouses. In addition, authors in [145] use UAVs to collect information on power lines in smart grids, which greatly reduces collection costs compared to traditional manual collection, and also ensures the safety of workers. UAVs are used for information acquisition, resulting in low costs and rapid examination of transmission lines [52].

3.2.2 *Industrial Factory Security.*
Due to the complex environment in factories and the high risk of safety supervision, accidents can directly bring serious economic damage and threaten lives of people. UAVs can be deployed flexibly in industrial factories to identify and provide timely feedback on safety hazards by learning algorithms. For example, an adaptive learning algorithm is leveraged to enable UAVs to discriminate and provide feedback on wall cracks on building surfaces [53]. Authors in [12] use UAVs to provide edge computing services to improve the safety incident handling capability in factories.

3.3 Emergency Scenarios

The solution for handling unexpected situations is always topical. For sudden disasters and network collapse, UAV networks can bring convenient and rapid solutions. Applications of UAVs in emergency scenarios mainly include rescue and search, information collection in disaster areas, material transportation, and aerial base stations and relays. In the following, we state excellent performance of UAVs in emergency scenarios from three aspects: geological disaster rescue, post-disaster network reconstruction and forest fire management.

3.3.1 Geological Disaster Rescue. How to efficiently and safely conduct rescue work in geological disaster areas always attracts much attention. Geological disasters, such as earthquakes and landslides, pose great difficulties and dangers on rescuers. ML enables UAVs to identify stranded people in disaster areas and collect geological information for analyzing disaster trends. Small UAVs can be used to detect people inside buildings in an earthquake and transport supplies in emergency areas where vehicles are not convenient [27]. In addition, geological hazards may continuously occur, such as aftershocks of earthquakes. Therefore, collecting geological information in the disaster area is necessary to guarantee the safety of rescuers and trapped people. Authors in [107] make use of UAVs to collect geological information from multi-hazard areas to grade the hazard. Authors in [101] design a UAV-assisted mobile crowd sensing system to collect and process data for disaster rescues. Furthermore, authors in [35] leverage UAVs combined with terrestrial laser scanning for landslide monitoring.

3.3.2 Post-Disaster Network Reconstruction. The recovery of communication networks after disasters is extremely important for the affected people and relief efforts. Rapid communication network restoration can not only reassure the affected people, but also provide necessary communications for disaster relief workers. Authors in [102] use UAVs as relays to restore communications in the disaster area through macro base stations. However, in most cases there are no available base stations in the vicinity of the disaster area. Authors in [115] construct a joint air-ground network based on both UAVs and vehicles as base stations to quickly restore networks in the disaster area, and use ML to optimize trajectories of UAVs and vehicles. Advantages of UAVs in disaster areas are obvious when road conditions in affected areas are harsh. UAVs are leveraged in [49] to provide emergency communication services when the locations of people in disaster areas are unknown, and ML is integrated to improve service capability. In addition, authors in [137] consider using UAVs to provide communication services and collect information from disaster areas, and employ ML to optimize trajectories of UAVs.

3.3.3 Forest Fire Management. Forest fires and wildfires are always concerned by researchers because of their imperceptibility, rapid development, abrupt changes and high hazard. UAVs are capable of real-time obstacle avoidance with the development of ML, and can be used for prevention and control of forest fires and wildfires. Authors in [98] propose to use UAVs to collect information on sensors deployed in forests to control and respond to fire situations in real time. UAVs can also be used to monitor fire tendencies to support fire suppression operations. Authors in [132] use UAVs to sense the persistent situation of forest fires and analyze fire development for potential emergencies in advance. Furthermore, authors in [24] propose to control multiple UAVs to detect and organize fire suppression in forest fires at the point of ignition.

Lesson 3: From the above application examples, it is clear that the Internet of UAVs has a wide range of applications in urban, industrial and emergency scenarios by integrating with MEC and ML. MEC enables UAVs to provide computation services and interactions in cities and industries, and extends interactions to the air. In addition, MEC enables UAVs to collect data from sensors to monitor fires in the forest. What's more, ML enables UAVs to be intelligent, not only optimizing their trajectories and energy management, but also enabling them with the capability of target identification and tracking for surveillance services. Finally, ML is promising to improve the offloading efficiency of MEC in different scenarios [84] [104] [93].

4 SOLUTIONS FOR MEC AND ML IN THE INTERNET OF UAVS

About 25 billion IoT devices are estimated to be in use by 2025, bringing new applications for IoT, such as real-time image analysis, and traffic information detection [131]. However, the huge amount of data requires IoT devices to be able to process and receive data in a timely manner [138]. The UAV is considered to be an indispensable role in the IoT, since it can help IoT devices solve the problem of insufficient computation resources. This section summarizes and discusses solutions for solving issues of MEC and ML in the Internet of UAVs and gives the corresponding lessons. A summary of solutions for MEC and ML in The Internet of UAVs is illustrated in Table 1.

Table 1. Summary of solutions for MEC and ML in The Internet of UAVs

Ref.	Description	Algorithms	Issues					Metrics		
			Dynamic Environment	Resource Limitations	Overloaded UAVs	Conflicting Metrics	Security	Delay	Energy Consumption	Throughput
[31]	A wireless powered MEC network with binary offloading	DRL	√	×	×	×	×	√	×	×
[55]	An energy-efficient multi-agent MEC network	MADRL	√	√	×	×	×	√	√	×
[96]	A multi-objective optimized trajectory control and offloading scheme	MARL	√	×	×	√	×	√	√	√
[141]	A multi-UAV and multi-ES MEC network for collaborative offloading	MADRL	√	√	×	√	×	√	√	×
[93]	A stochastic game-based offloading and resource allocation scheme	MADRL, TD3	√	√	×	√	×	√	√	×
[50]	A UAV and remote cloud collaborative offloading system	DQN	√	×	×	√	×	√	√	×
[7]	A multi-UAV-enabled uplink communication MEC network	DDPG, DQN	√	×	×	√	×	√	√	×
[57]	A maritime MEC network for latency minimization	DDPG	√	√	√	×	×	√	×	×
[86]	An MEC network that considers user equity services	MADRL	√	×	√	×	×	×	×	√
[17]	A potential game-based service allocation scheme	DRL	√	×	√	×	×	×	√	√
[34]	A secure offloading scheme that considers backdoor attacks	FDRL	√	×	×	×	√	×	×	×
[94]	A consortium blockchain-based secure offloading system	MADDPG	×	×	×	√	√	√	√	×
[71]	A semi-distributed secure offloading framework	FDRL	×	×	×	×	√	×	√	×
[36]	A heterogeneous offloading network combined with energy harvest	MADRL	×	√	×	√	×	√	√	×
[143]	A NOMA-assisted UAV offloading network	MADRL	×	√	×	√	×	×	×	√
[103]	An MEC network communicating in the terahertz band	DDPG	√	√	×	×	×	√	×	×

("√" if the solution satisfies the property, "×" if not)

4.1 Intelligent Computation Offloading

Since the UAV-enabled MEC network is dynamic, and the channel, user locations, and task volume are constantly changing, it is difficult to obtain offloading decision by traditional methods. Therefore, researchers employ ML-based methods to achieve intelligent computation offloading, and authors in [106] propose an optimization algorithm to achieve real-time trajectory control to minimize the total energy consumption of the system. The algorithm is based on DRL with two neural networks, one of which presents the specific trajectory of the UAV and the other network evaluates the action. In addition, a low-complexity matching algorithm is proposed to solve the user association and resource allocation problems. A DRL-based online offloading framework is proposed in [31] to solve the task offloading decision and time allocation problems in time-varying channels.

In addition, authors in [10] propose a space-air-ground offloading network, and utilize a DRL-based algorithm to learn offloading policies from the dynamic environment, in order to minimize the total system cost. To solve the curse of dimensionality, they propose an actor-critic algorithm based on policy gradient to improve algorithm efficiency. In addition, authors in [125] consider three offloading modes of UAVs, i.e., direct forwarding, coarse grained offloading, and fine grained offloading. Among them, direct forwarding refers to the UAV as a relay, coarse offloading means that the task is forwarded after simple processing such as noise reduction, while fine-grained offloading returns the task with complete processing. The authors propose a DQN-based algorithm to optimize the task completion time and the system cost.

However, single-agent ML algorithms need to deal with large-scale states and action spaces, leading to the increase of offloading latency. Authors in [4] transform the joint problem of computation offloading and data sensing into a partially observable **Markov Decision Process (MDP)**, and propose an algorithm based on **Multi-Agent RL (MARL)** to optimize the system energy efficiency and cost. Authors in [55] propose a multi-agent proximal policy optimization algorithm to realize dynamic decision making in MEC systems, with the objective of minimizing system energy consumption. In addition, they employ a ground-deployed digital twin to monitor the network status of MEC.

Since the computation demands of users are dynamic, authors in [79] consider the game between ESs and users, and propose an algorithm based on the strategy selection probability to minimize the system cost. Authors in [146] consider the correlation and topological constraints among tasks. They consider the bandwidth allocation of users and propose an MARL-based algorithm to minimize the average response time of tasks. Authors in [84] consider UAV and ground macro base stations to provide offloading services for vehicles with heterogeneous QoS requirements, and propose an **Multi-Agent DDPG (MADDPG)**-based algorithm to solve the computation resource allocation problem, to improve the throughput of the system.

Considering the stochastic fading channel and task requirements, authors in [3] propose a offloading framework based on Lyapunov optimization and DRL. In this framework, the optimization problem is modeled as a multi-level stochastic mixed-integer nonlinear programming, and Lyapunov optimization is employed to decouple the problem into deterministic subproblems. Finally, subproblems are solved by model-free DRL to maximize the average weighted total computation rate of the system. Considering the stochasticity of tasks and the time-varying nature of channels, authors in [56] formulate the problem of offloading decision and resource allocation as an MDP problem. DRL-based algorithms are proposed to solve the energy-efficiency optimization problem in distributed and centralized UAV-enabled MEC systems separately. In addition, considering the mobility of users, authors in [54] establish a Gauss-Markov model to predict the location of mobile users and propose a DRL-based algorithm to optimize the trajectory of UAVs and the QoS of users.

Lesson 4: ML is widely used in offloading decisions, resource allocation, and trajectory design for MEC in the Internet of UAVs. Nevertheless, MEC-based Internet of UAVs is highly dynamic and high-dimensional, and RL may fall into the curse of dimensionality. Therefore, DRL is generally used in the Internet of UAVs. The game among UAVs needs to be considered in multi-UAV scenarios. Thus, multi-agent ML algorithms, such as MARL and MADRL, can be considered for offloading decision to handle the cooperation and competition among UAVs. In addition, when the number of UAVs is large, a steep increase in the state and action space can be caused, and the training result is difficult to converge.

4.2 Efficiency Improvement

The limited energy and spectrum resources of UAV seriously affect the performance of MEC systems. Considering the energy limitation of UAVs and the high energy consumption of the model training of RL, authors in [91] propose a self-learning offloading strategy with a simplified decision process. The strategy uses time series and ML regression to predict future conditions. Compared with the RL-based offloading decision scheme, this scheme consumes less energy and also has an accuracy comparable to RL. To alleviate the energy limitation of UAVs, UAVs are equipped with energy harvesting units to obtain sustainable energy [36]. A distributed DRL-based offloading scheme is proposed to minimize the system cost. In addition, to enhance the cooperation among UAVs, the authors also propose a gated recurrent unit-assisted MADRL algorithm to optimize the offloading decision. In [63], UAVs offload tasks to ground ESs to extend the lifetime of UAVs, and a DRL-based algorithm is proposed to jointly optimize the offloading decision and flight direction. To minimize the energy consumption of UAVs, authors in [15] propose a DRL-based offloading framework. In this framework, a system controller is used to control the switch of the on-board computing elements or to offload tasks to other UAVs for processing.

Considering the spectrum limitation of UAVs, authors in [103] utilize terahertz technology to enhance the system capacity. Furthermore, they construct a physical channel model of the terahertz link, and formulate an optimization problem for joint resource allocation and computation offloading. Finally, they propose an algorithm based on double-DQN and DDPG to optimize the overall system delay. In addition, authors in [143] employ NOMA to improve the spectral efficiency of UAV-enabled MEC systems and propose a multi-agent mutual DQN-based algorithm to optimize UAV trajectories and resource allocation. To address user mobility, they propose a K-means-based algorithm to cluster users and determine the dynamic decoding order periodically. Specifically, the optimization problem is solved in two stages. The first stage determines user clusters to obtain user associations, and the other one optimizes trajectories and power allocation to optimize the total system throughput.

Lesson 5: Existing solutions for energy efficiency improvement of UAVs mainly focus on optimizing energy consumption and energy harvesting, where energy harvesting solutions such as wind and solar energy are designed in [36]. However, wind and solar energy harvesting depend on the environment [108] and are unstable, which may result in degradation of system performance. Although NOMA technology can improve spectrum utilization by allocating a sub-channel to multiple users, it increases the complexity of receivers, which is not friendly to UAV-enabled MEC systems. Furthermore, the consideration of decoding order complicates the offloading optimization problem.

4.3 Channel Condition Amelioration

The dynamic channel condition and the emergence of high-rise buildings in cities greatly affect the computation services provided by the Internet of UAVs [139]. It is possible to obtain better channel conditions by adjusting the trajectories of UAVs. Authors in [43] incorporate the consideration of wireless channels in the trajectory design of UAVs, adjust the position of UAVs to obtain the best channel condition, and solve the joint problem of trajectory design and resource allocation by leveraging **Successive Convex Approximation (SCA)** and Dinkelbach method to maximize the energy efficiency of the system. In addition, authors in [136] consider the quality constraint of the communication link between UAVs and users, which is determined by the minimum received signal-to-noise ratio. It uses a graph-theoretic approach to solve the flight delay optimization problem. However, the height in the actual environment affects the channel conditions of the UAV, and the building shading in the city is closely related to the height. Authors in [14] consider the actual environment where the LoS channel condition probability appears. It uses **Block Coordinate Descent (BCD)** and SCA to optimize the communication efficiency.

The use of IRS to enhance UAV communication is gradually being studied. However, the use of IRS to assist UAV communication has two main challenges. One is channel estimation and tracking, where the channel conditions of UAVs are variable and require estimation and tracking [130]. The other is the design of the reflection factor, i.e., the phase shift matrix in the Internet of UAVs [69]. Authors in [130] consider channel tracking and estimation for UAV-IRS in 3D dynamic scenes, and use DL-based algorithms to improve the performance of channel tracking. Considering different IRS reflection units, interference among different IRS reflection units is resolved in [47] by counting propagation phases. IRS propagation phases are aligned using strong components to achieve the improvement of the received signal strength and the reduction of multi-path effect. Wireless communications are vulnerable to attacks, and thus the security of UAV communications is important. Authors in [97] consider elevation angle dependent probabilistic channels that are relevant to the actual scenario. They propose a beamforming and semidefinite relaxation approach to jointly optimize LoS path losses and UAV trajectories, and use **Alternating Optimization (AO)** to improve the secrecy rate of the system. Considering

UAV wideband systems, IRS is applied to UAV communication system with OFDMA. AO is leveraged in [113] to optimize IRS scheduling, UAV trajectories, and resource allocation to improve the data transmission rate.

For the design of the reflection factor, authors in [69] use IRS to enhance the NOMA communication of the UAV, consider the decoding order of NOMA, and use BCD and SCA to maximize the data transmission rate of the system. Considering power transmission limitations, trajectory design, resource allocation and reflection matrix of the IRS, BCD is leveraged in [139] to decouple the formulated optimization problem into three sub-problems to maximize the data transmission rate. Similarly, authors in [69] use IRS to enhance the NOMA communication of UAVs, consider the decoding order of NOMA, and use BCD and SCA to maximize the data transmission rate of the system. Authors in [66] consider IRS using uniform planar array, and jointly optimize the trajectory of UAVs and the phase shift of IRS, based on double-DQN and DDPG, aiming to maximize the gain of wireless communications in the Internet of UAVs. In addition, authors in [83] consider the joint channel estimation and reflection factor design, integrate the phase shift and transmit beamforming of IRS, and consider the flight trajectory of UAVs for optimization. In order to maximize the average secrecy rate, the problem is decomposed into three sub-problems. They apply AO to solve transmit beamforming, leverage fractional programming method to solve the phase shift matrix of IRS, and use SCA to optimize the UAV trajectory.

Lesson 6: Most of existing studies consider the ideal LoS scenario and the static access of the user, which is not consistent with the actual application scenario. The flight altitude of UAVs in the actual environment affects the channel conditions of the wireless communication. For example, different altitude obstructions affect the LoS path between UAVs and users. Therefore, when modeling the flight space of UAVs, 3D space should be considered. In addition, it is necessary to consider the impact of UAV mobility on the channel, i.e., considering the stability of the wireless channel. What's more, security and failure scenarios are also necessary to be considered. The current research mainly focuses on the channel estimation and reflection factor design between IRS and UAVs. However, IRS scheduling design also needs to be considered. A reasonable IRS scheduling can not only accommodate the dynamic amount of users in the Internet of UAVs, but also avoid IRS overloading.

4.4 Load Balance

To solve the problem of surging tasks in some regions served by UAVs, authors in [20] use parallel offloading among UAVs to achieve load balance. Due to the existence of dimensionality curse, the authors propose an algorithm based on DRL to optimize the QoS of users. An algorithm based on multi-armed bandit is used to select the optimal multi-hop path to maximize the system utility [70]. Authors in [114] use discrete Stackelberg game to solve computation offloading and UAV deployment problems in hierarchical UAV-MEC systems. The UAV can be used as ESs and relays in this game, and the authors propose a hierarchical learning framework to reach Stackelberg equilibrium.

Considering the limited resources of UAVs, authors in [57] propose a two-layer MEC architecture for regulating the load among UAVs. Specifically, when the low-layer UAVs are overloaded, their tasks can be offloaded to the upper-layer UAVs for processing to reduce task latency. The architecture can also determine the number of virtual machines based on tasks to further improve offloading efficiency. Authors in [105] propose an MADRL-based algorithm to optimize the geographic fairness and the load among UAVs to minimize the system energy consumption. In particular, geographic fairness can reflect the level of user QoS at the current time. Moreover, the trajectories of UAVs are planned by a low-complexity algorithm.

Besides, the fairness of users also needs to be considered. Considering the fairness problem caused by the varying channel environments, authors in [86] employ proportional fairness scheduling to set the time-varying weights of users between users and UAVs. Specifically, this problem is formulated as a weighted throughput maximization problem and can be transformed into MDP. Furthermore, the authors propose an MADRL-based fairness throughput optimization algorithm to solve the problem. An MADDPG-based algorithm is put forwarded to solve the trajectory optimization and user association problem, with the purpose of improving system energy efficiency [17]. The potential game is introduced in the association problem of multiple UAVs and users to reduce the computation complexity and the system cost. Authors in [142] propose to predict user behaviors to avoid UAV overloading to maximize the total system throughput. The load balance of UAVs is realized by a distributed framework, and an active mobility management solution is used to predict trajectories and requests of users.

Lesson 7: Existing solutions to realize load balance among of UAVs are mainly achieved by parallel offloading among UAVs. However, the transmission of information among UAVs also causes certain latency, and it cannot ensure that there are always idle UAVs near the overloaded ones. For this reason, it is promising to analyze the historical information and predict the future state of users to improve the system performance.

4.5 Multi-Objective Optimization

The conflict among different optimization metrics is typically relieved by constructing a multi-objective optimization problem and then trying to reach a balance by designing an efficient optimization algorithm. Authors in [7] consider the trade-off between delay and energy consumption, and formulate the weighted sum of the two metrics as a computation cost minimization problem. The authors use algorithms based on DDPG and DQN to solve the trajectory and association optimization problem of UAVs, respectively. Similar to [7], authors in [92] also consider the computation cost minimization problem, and propose a DDPG-based MEC framework to optimize the offloading policy and resource allocation. In this framework, a UAV cluster head exists to act as an agent, training the local model to find the optimal action. Furthermore, in order to cope with the continuous action space, the authors employ a central network controller to train the global model and then reduce the action space on the UAV cluster head.

In addition, authors in [50] decompose the cost minimization problem into three subproblems, i.e., UAV deployment, resource allocation, and offloading decision problems. For the former two subproblems, sequential convex programming and sequential quadratic programming are used to solve them, respectively. Because the offloading decision problem contains decision variables, it is solved by the DQN algorithm. Furthermore, different delay and energy consumption weights are given to users for preference representation. Similar to [50], authors in [141] assign weights to both energy consumption and delay in the total computation cost. They use MEC and ground ESs for collaborative service delivery, propose a collaborative offloading framework based on MADRL, and utilize TD3 algorithm to solve the problem of high-dimensional continuous action space.

Authors in [38] consider the balance of latency and energy consumption, and evaluate the QoS of users by the gap between their maximum tolerated latency and the actual latency. Since this problem is oriented to a multi-UAV-enabled MEC network, it is transformed into a multi-agent MDP. In this system, each UAV is an agent and is optimized by the MADDPG-based algorithm. Authors in [93] transform the minimization system cost problem into a stochastic game, and propose an MADDPG-based algorithm to solve the game. Specifically, the algorithm learns the optimal policy in a dynamic environment, and reduces the model training cost by centralized training and decentralized execution.

Authors in [96] consider the balance of three optimization metrics, i.e., latency, energy consumption, and throughput, and formulate it as a weighted sum problem. Then, the problem is transformed into a multi-objective Markov problem, and solved by an evolutionary RL-based algorithm. The algorithm can output multiple non-dominated policies simultaneously to satisfy different user preferences.

Lesson 8: The main optimization metrics in UAV-enabled MEC systems are energy consumption, latency, and throughput, and these conflicted metrics are usually weighted and then summed for optimization. However, the weighted sum usually has bias and affects the balance of metrics. In this regard, multi-objective learning algorithms are always leveraged, but user heterogeneous QoS requirements need comprehensive considerations.

4.6 Security and Privacy

The open communication environments of UAVs expose the offloading of users to the risk of eavesdropping and the heterogeneous network raises the privacy leakage problem. To solve the security problem for UAV computation offloading and energy harvesting, authors in [94] propose a consortium blockchain with smart contracts to decentralize resource allocation between users and UAVs, and secure transactions. Specifically, the consortium creates accounts with public parameters and uniquely identifies addresses for the entities involved in the computation, such as UAVs, and encrypts keys. In addition, the authors transform the task offloading problem into a Stackelberg game, and use an MADDPG-based algorithm to optimize the offloading decision for the minimization of the system cost.

Some studies utilize ground jammers to improve the system security. Authors in [60] deploy ground jammers to send jamming messages to secure the transmission of MEC systems. Considering data queue stability and basic computation requirements, offloading decision and resource allocation are jointly optimized. The former is generated by DNN and the latter is optimized by SCA algorithm to maximize the system efficiency. Authors in [61] consider the heterogeneous requirements of users, and use MARL to improve the security of MEC system to optimize the system utility. Among them, the UAV deployment is optimized by the spiral placement method, and the ground jammer is used to interfere the jammer UAV.

Federated learning has advantages in data privacy. Authors in [11] propose a federated DRL-based framework to optimize task offloading and power allocation policies, to reduce the total system cost while securing data privacy. Specifically, the optimization problem is modeled as an MDP and optimized by DRL. To prevent frequent training of DRL from compromising user privacy, the authors use **Federated DRL (FDRL)** to improve the security of the MEC network. Authors in [71] propose a centralized MARL-based algorithm for offloading decision making and resource allocation to minimize the sum energy consumption. To solve the privacy problem caused by the large amount of centralized data, the authors propose a semi-distributed MARL scheme, and Gaussian differentiation is used to protect the data privacy of users.

Although, ML is capable to interact with the dynamic environment, it is vulnerable to attacks. Authors in [34] propose a FDRL-based algorithm to optimize the offloading policy and ensure the data privacy of users, and leverage DQN to solve the curse of dimensionality. Furthermore, considering that the sharing of model parameters in FDRL is vulnerable to the backdoor attack, the authors propose a new triggerless backdoor attack scheme to perform a backdoor attack against the reward function, and propose a lightweight agnostic defense mechanism to demonstrate its effectiveness.

Lesson 9: The methods used for secure offloading in UAV-enabled MEC networks mainly include blockchain, ground jammers, and federated learning. However, the blockchain may increase the offloading latency, which is unacceptable for latency-sensitive missions. Ground jammers need to be deployed on the ground, and it is difficult to ensure the real-time security of communications in dynamic scenarios. Moreover, ML such as RL has the risk of backdoor attacks [34], and thus appropriate defenses need to be deployed against these attacks.

4.7 Neural Layer Offloading

ML inference requires a large amount of computation resources, and thus a huge delay can be caused when it is executed on mobile devices, such as UAVs with limited computation resources. Therefore, recent studies concentrate on dividing neural layers and offloading them to nearby or remote devices to speed up the training process of ML. A distributed collaborative reasoning scheme is proposed in [33], to reduce latency and energy consumption by offloading DNN partitions to heterogeneous end devices for training. In addition, the authors design a DRL-based dynamic task assignment algorithm to further reduce latency. An offloading model for chained DNNs is proposed in [18], and an improved depth-first search algorithm is presented to obtain optimal offloading decisions, which has a significant reduction in task latency. In addition, authors in [144] propose a partial offloading scheme, which processes DNN layers in parallel, and leverage particle swarm optimization to schedule resources and make offloading decisions of the fusion layer, while preventing local optima, to reduce DNN inference latency.

Using ESs at the network edge to offload DNN inference tasks can also reduce the inference latency. Authors in [9] construct a model to extract the structure of DNNs. Then, a random forest regression algorithm is utilized to estimate and partition to reduce the cost of each neural layer. After that, an appropriate layer is selected for offloading, to reduce system delay. Authors in [32] propose a DNN partitioning, offloading and scheduling strategy, which can offload the high-intensity DNN inference to ESs for processing and minimize the inference latency in mobile networks. Authors in [118] formulate DNN offloading as a multiple assignment problem with the purpose of proportional fairness maximization, and propose a distributed offloading scheme at the network edge to accelerate inference. Authors in [122] propose a scheme for edge and cloud collaborative DNN offloading, in which PSO-GA algorithm is introduced to optimize inference delay. In addition, a layer merge uploading algorithm is proposed to optimize partitioning and uploading. Authors in [39] consider static and dynamic network environments, and propose a DNN-based inference offloading framework, in which adaptive partitioning and sizing of DNNs is performed.

The energy consumption of offloading is also a hot topic. A fine-grained elastic partitioning mechanism is proposed in [89], to partition distributed DNNs in 5-Generation networks. The combination of MEC and device-to-device techniques is considered to achieve the optimization of both delay and energy consumption of DNN inference. Authors in [13] propose a DNN adaptive partitioning method for the collaboration between IoT devices and ESs, and design a Liapunov-based algorithm to assist devices in offloading DNN tasks, to achieve the optimal reduction in total system cost and latency. Authors in [19] propose a hierarchical partitioning strategy for DNN partitioning and use a DNN latency prediction model to demonstrate the difference in latency between local and edge computing of tasks. In addition, authors in [123] consider coupled coordination, reduce the differentiation among metrics, and optimize the load balance among edge nodes. They propose a local-edge-cloud collaborative algorithm, which aims to improve DNN computation efficiency and the minimization of energy consumption. Considering the collaboration among the cloud, the web and the edge, authors in [88] propose a DNN layering method based on DDPG to achieve low latency and low cost for task processing.

Due to insufficient computation resources, DNNs require some compression to sacrifice accuracy [8]. Authors in [99] propose a confidence-based offloading framework, and use an adaptive scheme to decide which parts to offload to guarantee DNN accuracy. Authors in [58] consider partial offloading of DNN inference tasks for multiple streams, and propose an adaptive MEC inference framework to dynamically divide and schedule tasks. In addition, authors in [121] propose a learning-based dynamic offloading method for DNN inference, and an approximate algorithm based on random rounding technique is designed to optimize total system energy consumption and the number of inference requests. Authors in [40] consider inference acceleration of delay-sensitive DNNs, and design an online algorithm to schedule DNN offloading tasks, to maximize the system throughput. Authors in [81] consider DL-based offloading of vision tasks on UAVs. By considering the noise in wireless channels, the authors propose a DL-based denoising network to improve QoS.

Lesson 10: Researchers design various DNN layering strategies and leverage MEC to meet the high computation demand of ML. However, since the application scenarios of UAVs are dynamic, static DNN layering is difficult to meet the requirements of users. In addition, the computation offloading game problem in dense-user scenarios with multiple UAVs and multiple ESs needs to be further investigated.

5 RESEARCH CHALLENGES AND OPEN ISSUES

Although we have introduced the latest progress in the Internet of UAVs, and summarized existing solutions in previous sections, challenges still exist in the Internet of UAVs. In this section, we discuss several open issues for future research.

5.1 Security Issues in The Internet of UAVs

The MEC-based Internet of UAVs is highly heterogeneous and vulnerable to attacks [48], and some researchers have considered the corresponding security issues. For example, authors in [2] add a secure channel capacity constraint to the offloading optimization problem to improve system security from the physical layer. However, this scheme limits the channel capacity and only considers the communication security. Blockchain, as a distributed and popular secure technology, has excellent performance in the field of information security [76]. For distributed heterogeneous networks prone to attacks, the blockchain can use consensus mechanism to authenticate devices, and manage legitimate nodes to prevent the intrusion of malicious nodes. In addition, in terms of data security and privacy, the anonymity and encryption technology encrypts the communication data between UAVs and IoT devices, which makes it difficult for malicious eavesdroppers to obtain information and locate users. Therefore, the employment of blockchain in the MEC-based Internet of UAVs to improve security is worth of study.

Although the blockchain can achieve an improvement in the security of the Internet of UAVs, it also brings some challenges. For example, it increases energy and computation resource consumption of UAVs [127], which is challenging for UAVs with scarce energy and computation resources. In addition, the mobility of UAVs and IoT devices can lead to frequent access and disconnection of users. The large number of dynamically accessed users raises the design difficulty of blockchain applications in the Internet of UAVs. In addition, it causes latency and limits throughput of the Internet of UAVs. Therefore, it is rather challenging to adapt the blockchain to the dynamic Internet of UAVs.

5.2 IRS-enabled Wireless Channels in The Internet of UAVs

Most studies assume LoS channels with known channel conditions between UAVs and IoT devices, which is not consistent with the real-world environment. In addition, some studies reduce the interference caused by NLoS by leveraging NOMA technology to the Internet of UAVs. However, NOMA increases the architecture complexity of receivers in exchange for spectrum utilization improvement, which is not friendly to resource-limited UAVs and IoT devices. IRS can be utilized to build a virtual LoS channel between UAVs and IoT devices to avoid obstructions [139].

Although IRS technology is a promising solution to the NLoS path problem in the Internet of UAVs, it is challenging to integrate IRS with UAVs to assist NLoS communications. The channel information in the Internet of UAVs is imperfect and dynamic, and it is a challenge to perform channel estimation. In addition, although IRS is low-cost, its resource is limited, and it is challenging to make reasonable IRS resource allocation by considering the flexible characteristic of UAVs. Furthermore, since the IRS is exposed to the outside environment and vulnerable to interference and damage from the environment, it is a challenge to solve security issues of IRS-based Internet of UAVs.

5.3 Collaborative Offloading of Multiple UAVs in Dynamic Environments

In the Internet of UAVs, UAVs are dynamic and required to be environment-aware. Meanwhile, the users served by UAVs are also dynamic, and the locations of UAVs as well as users are changing. Multi-UAV scheduling is different from single one, which needs to consider the collaboration and competition among UAVs. Currently, MADRL and MARL are effective in solving the above problems, enabling UAVs to have the ability of environment awareness and intelligent decision making.

However, some issues are still challenging. For example, although MADRL can solve the dynamic offloading and gaming problems of UAVs, it will increase the energy consumption of UAVs, which may reduce the lifetime of UAVs. In addition, the current considerations are mostly about offloading decisions between small-scale UAVs and users, while ignoring the convergence of algorithms and the unstable environment for large-scale users. Furthermore, communication channel conditions among UAVs, such as sudden disconnection of some UAVs in the service process, are not fully taken into account. What's more, by extending multi-UAVs to 3D scenarios with the addition of height factor, joint offloading decision and trajectory design are still challenging.

5.4 Balances among Various Metrics for UAV-Enabled MEC Systems

In UAV-enabled MEC systems, optimization metrics include latency, energy consumption and throughput. Although various metrics are considered, there are only a few studies considering heterogeneity requirements of users. Specifically, existing solutions generally construct a weighted sum of different preferences of users. However, weights of different users are generally arbitrarily set, which may be unfair to users. In addition, for throughput optimization, some users with poor channel conditions may not be permitted to access the system to maximize the system utility. Therefore, we need to pay more attention to user QoS in the UAV-enabled MEC system rather than just pursuing system benefits. In addition, most current algorithms are based on single policy and cannot output multiple preferred policies at the same time. Multi-policy learning algorithms can provide a set of Pareto optimal strategies for decision makers, which are helpful to solve the problem of heterogeneous services in MEC systems.

5.5 Energy Efficiency in UAV-Enabled MEC Applications

How to reduce energy consumption and improve the lifetime of UAVs in MEC applications has been a hot topic. The current research on single UAV-enabled MEC has almost matured and has limited performance improvement in terms of energy consumption. Therefore, it is necessary to further reduce the overall energy consumption by jointly scheduling UAVs and tasks in MEC systems.

However, using multiple UAVs to realize MEC still faces several challenges. In practical design, it is necessary to consider the distance between UAVs and terminal users, as well as available computation resources of UAVs. In addition, energy consumption of UAVs and the latency tolerance of users should be taken into account. It is challenging to optimize the overall energy consumption of UAVs while considering all these issues together. Moreover, we need to consider obstacles in the environment where UAVs provide edge computing services may cause NLoS channel, so that the change of UAV location further increases the complexity of the problem.

6 CONCLUSION

We present a comprehensive survey on technologies, applications, solutions and challenges of the Internet of UAVs, focusing on the integration of ML and MEC. First, we briefly introduce the background of the Internet of UAVs. Then, we summarize key techniques in MEC and ML being applied to the Internet of UAVs, and provide architectures and issues for the integration of MEC and ML in the Internet of UAVs. After that, we present applications of the Internet of UAVs integrated with MEC and ML in different scenarios. We categorize and discuss the corresponding solutions based on the issues of MEC and ML in the Internet of UAVs. Finally, several future research directions and open issues are given.

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