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Review

Task offloading and optimization methods in UAV-enabled mobile edge computing: A comprehensive survey

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ABSTRACT

The surge in compute-intensive and latency-sensitive applications such as autonomous driving and smart cities is straining traditional cloud computing. Recent advancements in Mobile Edge Computing (MEC) and the emergence of Beyond 5G (B5G) technologies have catalyzed the integration of Unmanned Aerial Vehicles (UAVs), heralding UAV-enabled MEC as a transformative paradigm. By utilizing UAVs as flexible aerial edge servers or relays, MEC can bring computational resources closer to end-users, thereby reducing latency and enhancing service quality. Despite their advantages, challenges remain regarding task offloading, specifically, determining when, how, and whether to transfer computational tasks from user devices to UAV-MEC servers for remote processing. UAV constraints, offloading strategies, communication channels, and energy consumption complicate the task offloading process. Therefore, sophisticated optimization strategies are essential to balance latency, energy consumption, task completion rates, and overall system efficiency. This survey paper focuses on task offloading strategies and optimization methods for UAV-enabled MEC networks. We discuss potential UAV-enabled MEC architectures, focusing on the interactions between UAVs operating within the MEC framework and ground users, as well as communication channel access. We present task offloading methods and optimization techniques. Although UAV-enabled MEC holds great promise, it still faces challenges that need to be addressed to support a broader range of applications. We highlight research issues and future opportunities, divided into three levels based on the real-world deployment of UAV-enabled MEC, moving from those most critical to those important for optimization and scale.

Contents

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1. Introduction

The significant growth in mobile users worldwide led to a surge in data traffic over the past few decades. The Ericsson Mobility Report, released in June 2023, projects that global Fifth Generation (5G) mobile subscriptions will reach 1.5 billion by the end of the year. Many mobile applications, including virtual reality and video transmission, require networks that can handle real-time delays. To address these challenges, Mobile Edge Computing (MEC) technology has been introduced. MEC brings information technology services and cloud computing capabilities closer to mobile devices within the Radio Access Network (RAN) [1]. This approach positions computing resources at the network's edge, near the mobile devices. As defined by the European Telecommunications Standards Institute (ETSI), MEC is an emerging technology that can improve the quality of service provided by mobile operators and mitigate issues related to cloud computing.

Unmanned Aerial Vehicles (UAVs) significantly enhance communication by serving as aerial base stations and airborne mobile devices within cellular networks [2], as well as functioning as relays [3] and acting as MEC servers [4]. The applications, challenges, and unresolved issues associated with UAVs in wireless systems still exist [5]. UAVs can be categorized by various parameters such as size, range, altitude, type, rotors, landing mechanisms, and aerodynamics [6].

The future integration of UAV and MEC with Beyond 5G (B5G) or Sixth-generation (6G) networks promises to increase data rates further and minimize delays. It examined the application of UAVs within wireless communication networks. It discussed how they served as wireless power transmitters, relay nodes, MEC servers, and aerial base stations for information gathering and sharing. The research examined wireless networks using UAVs and identified areas requiring further attention, including channel modeling, interference mitigation, and leveraging machine learning and artificial intelligence [7]. It is particularly critical for the Internet of Things (IoT), which aims to connect vast networks of devices to enable smart applications. Since these devices, including UAVs, often have limited computing power and prioritize battery life and mobility [8,9], transmitting data to remote servers for processing is an essential strategy to reduce their workload. Collaboration between UAVs and MEC aims to minimize latency, maximize throughput, and ensure fair resource allocation among users [10]. To enhance computation rates, factors such as UAV positioning and task offloading techniques must be considered. This is especially crucial in post-disaster scenarios, where strategically positioning UAVs to maximize computational efficiency is essential [11].

Therefore, developing effective methods for task offloading in UAV-enabled MEC is critical. UAVs involve decisions on whether to process tasks locally or on an edge server to optimize delay and energy [12]. The concept of a UAV-enabled MEC has been introduced, with reliability-aware computational offloading [13]. Several algorithmic approaches have been proposed, including techniques for resource partitioning [14], as well as offloading mechanisms [15] designed to minimize mobile user energy consumption. Effective cache scheduling and buffer management are also vital; through cooperative computation with Base Stations (BS), UAVs can reduce total endurance time and ensure timely updates [16]. Furthermore, the integration of MEC services with UAVs can effectively decrease delays and enhance network throughput. Besides, jointly optimize UAV deployment (stop points and associations) and flight trajectories to minimize energy consumption by utilizing combinatorial and continuous optimization techniques, along with decomposition methods [17]. Despite these advancements, significant challenges remain for practical implementation. Offloading tasks across different service provider MEC servers is non-trivial, and managing systems with multiple UAVs and MEC servers adds further complexity. Moreover, security presents a major risk, as improper eavesdropping during offloading between ground users and UAVs can expose sensitive location data [18].

Several existing surveys have addressed task offloading and optimization in UAV-enabled MEC [19–31]. However, these works have the following limitations:

Table 1
The list of abbreviations and their definitions.

Abbreviations	Definitions	Abbreviations	Definitions
3-D	Three Dimension	5G	Fifth Generation
6G	Sixth Generation	B5G	Beyond Fifth Generation
4G LTE	Fourth Generation Long-Term Evaluation	H2O	Hybrid learning based Online Offloading
AI	Artificial Intelligence	AP	Access Point
BS	Base Station	BCD	Block Coordinate Descent
CDMA	Code Division Multiple Access	CNN	Convolutional Neural Network
CCCP	Concave Convex Procedure	CB-UCB	Combinatorial Bandit Upper Confidence Bound
DL	Deep Learning	DP	Dynamic Programming
DRL	Deep Reinforcement Learning	DDPG	Deep Deterministic Policy Gradient
ETSI	European Telecommunications Standards Institute	FDMA	Frequency Division Multiple Access
FHSO	Flexible-Hybrid Subtask Offloading	FL	Federated Learning
HMTD	Hierarchical ML Task Distribution	IoT	Internet of Things
ILP	Integer Linear Programming	IP	Integer programming
KKT	Karush-Kuhn–Tucker	LoS	Line-of-Sight
ML	Machine Learning	MDP	Markov Decision Process
MIMO	Multiple-Input Multiple-Output	MINLP	Mixed-Integer Non-Linear Programming
MO	Multi-Objective	MEC	Mobile Edge Computing
MC	Mobile Clones	NLP	Non-Linear Programming
NSGA-III	Non-dominated Sorting Genetic Algorithm III	NP	Non-deterministic polynomial time
NOMA	Non-Orthogonal Multiple Access	OFDMA	Orthogonal Frequency Division Multiple Access
PSO	Particle Swarm Optimization	PACED-5G	Predictive Acceleration Control Edge Device for 5G
QCQP	Quadratically Constrained Quadratic Program	QoS	Quality of Service
RIS	Reconfigurable Intelligent Surface	RAN	Radio Access Network
SDN	Software Defined Networking	SCO	Successive Convex Optimization
SCP	Successful Computation Probability	SAGIN	Space-Air-Ground Integrated Network
SCA	Successive Convex Approximation	TDMA	Time Division Multiple Access
UAV	Unmanned Aerial Vehicle	URLLC	Ultra Reliable Low-Latency Communication
UEPSSL	User Equipment Probability-based Strategy Selection Learning	UAVPSSL	Unmanned Aerial Vehicle Probability-based Strategy Selection Learning
WPT	Wireless Power Transfer		

- The survey [19] focuses exclusively on game theory methods for modeling and analyzing UAV-enabled MEC. In contrast, study [20] addresses latency, energy efficiency, and security, while [21] explores latency, connection density, data transmission rates, energy optimization, mobility, and scheduling mechanisms.
- The survey [22] investigates latency, energy consumption, and execution time delays. Meanwhile, [23] addressed energy efficiency, resource allocation, UAV trajectory, latency, and security in UAV-enabled MEC.
- The survey [24,25] examine resource management in UAV-enabled MEC. However, [26] provides a comprehensive overview of resource optimization techniques in UAV-assisted wireless networks, emphasizing UAV placement, resource allocation, and spectrum sharing.
- The survey [27] investigates core research topics, techniques, and categories of tasks related to offloading. In contrast, studies [28, 29] examine the impact of computational resources and battery life when offloading tasks to nearby mobile MEC units.
- The survey [30] discusses optimization strategies that employ Machine Learning (ML) techniques in UAV-enabled MEC. Meanwhile, [31] examines how the integration of AI with UAVs can enhance data offloading in MEC environments.

Table 1 summarizes all the abbreviations and their definitions used throughout the survey.

1.1. Motivation and contribution

Task offloading optimization strategies in UAV-enabled MEC systems take a comprehensive approach to address the limitations of UAV-based networking environments while enhancing system efficiency, resource consumption, and user satisfaction. These strategies utilize optimization theory, machine learning, and networking protocol algorithms to manage the dynamic allocation of computational tasks between MEC servers and UAVs. This process must account for a complex set of dynamic factors, including task characteristics, UAV mobility, ground user mobility, MEC or UAV deployment, and energy constraints. A key component is the task scheduling algorithm, which evaluates variables like latency, energy consumption, and computation offloading decisions based on real-time data analytics. However, existing surveys on UAV-enabled MEC have largely overlooked task offloading and optimization techniques, focusing instead on network architecture and channel access. Even recent developments in distributed optimization lack a thorough review. This paper addresses this oversight by comprehensively surveying task offloading strategies and optimization techniques.

The contributions of this survey paper are as follows:

1. We review the state-of-the-art UAV-enabled MEC, focusing on network architecture, task offloading strategies, and optimization techniques.
2. We examine five potential network architectures for UAV-enabled MEC systems, outlining their key enablers, the function of UAVs as aerial edge servers, and the major challenges in their deployment and operation.
3. We provide a decision flowchart of computational offloading mechanisms and a comprehensive taxonomy of task offloading in UAV-enabled MEC.
4. We provide a comprehensive and unified taxonomy of optimization methods in UAV-MEC systems, categorizing them based on the core problem they address. Additionally, we provide a critical analysis of their applicability and the performance trade-offs involved.
5. We highlight important open research challenges, particularly those relevant to the recent emergence of B5G and the upcoming 6G, as well as the evolving roles of UAVs and MEC in realizing these advanced systems.

1.2. Organization of survey

The remainder of this survey is structured into the following sections: Section 2 offers a comprehensive review of existing surveys. Section 3 presents a detailed analysis of the architecture of UAV-enabled MEC. Section 4 examines the communication channels within UAV-enabled MEC. Section 5 addresses task-offloading techniques for

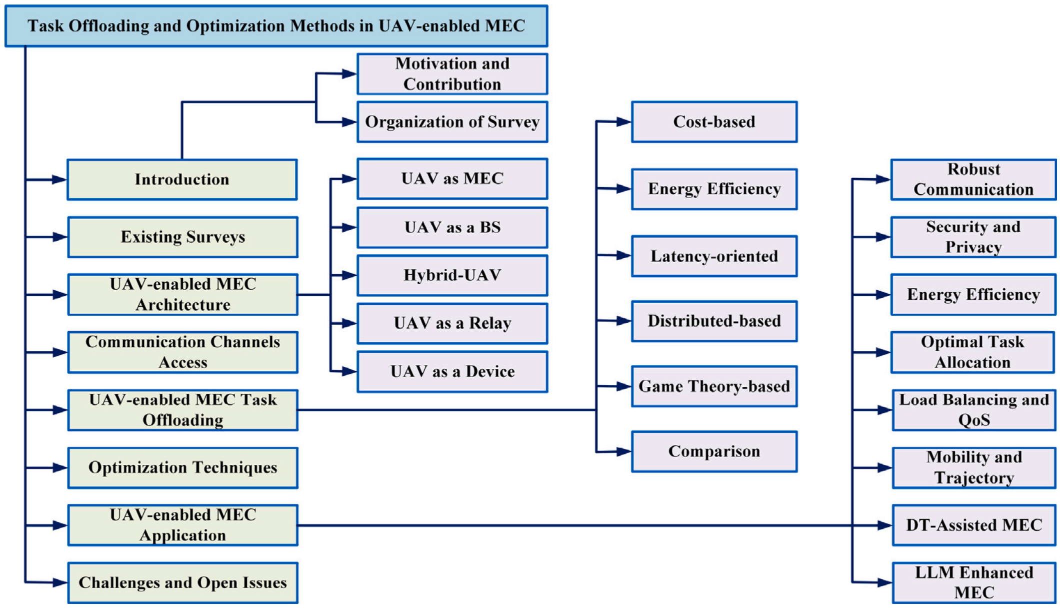

Fig. 1. Survey organization.

UAV-enabled MEC. Section 6 discusses optimization techniques for task offloading and energy efficiency in UAV-enabled MEC. Section 7 explores the applications of UAV-enabled MEC in wireless communication. Section 8 highlights key challenges and open issues related to task offloading and optimization. Finally, Section 9 concludes with a summary of the survey.

Fig. 1 provides a detailed overview of the survey organization.

2. Existing surveys

Yazid et al. [20] examine various aspects of UAV-enabled MEC, including services, architecture, latency, task offloading, energy demand, security, and current research trends. Their work provides insights into future applications in the IoT field, emphasizing the roles of Deep Learning (DL) and ML. However, this study does not discuss channel access, optimization techniques, cost-based task offloading, latency-oriented task offloading, distributed task offloading, and game-theory-based task offloading in UAV-enabled IoT networks.

Mkiramweni et al. [19] investigate game theory methods for UAV-enabled MEC. Their focus includes architecture, optimization, energy efficiency, and the challenges associated with these methods. They also classify game-theory approaches within the task offloading taxonomy. However, the scope of this study does not cover all the taxonomy and optimization methods in UAV-enabled MEC.

Fatima et al. [21] review the integration of MEC with UAVs and emerging wireless technologies. This study presents a taxonomy of UAV-enabled MEC and discusses key factors, including architecture, latency, energy efficiency, security, and resource allocation. However, the study does not discuss the channel access mechanism of wireless technology and the optimization method used in UAV-enabled MEC.

Huda and Moh [22] examine computational offloading techniques and architectural design challenges, focusing on task offloading algorithms in UAV-enabled MEC. This thorough review sorts and compares the pros and cons of the most advanced algorithms, along with the situations in which they work best. Decisions for binary, partial, and load-relaying offloading each have their own approaches to design and implementation. However, this study does not address the task offloading taxonomy and optimization techniques, nor does it consider the usefulness of current solutions. Critical issues such as dynamic multi-UAV coordination, energy constraints, and mobility management in large or dense network environments were not discussed.

Adnan et al. [23] investigate design issues related to energy efficiency, resource allocation, UAV trajectory, latency, security, and privacy in UAV-enabled MEC, and identify key challenges. However, this study does not focus on the taxonomy of task offloading and optimization techniques, including details on distributed task offloading and game-theory-based offloading.

McEnroe et al. [24] provide a detailed overview of how AI can be used in edge networks, focusing on how it can simplify channel access, save energy, and improve the performance of UAV systems. The study states that the main pros and cons of using edge AI are better network responsiveness and problems with system integration. However, this study does not address task offloading and optimization methods.

Xia et al. [25] examine resource management in UAV-enabled MEC, detailing the architecture, key research directions, techniques, taxonomy, and performance indicators. However, this study does not discuss task offloading, applications, and optimization methods.

Basharat et al. [26] provided an overview of ways to use resources in UAV-enabled wireless networks better, focusing on where to deploy UAVs, how to share resources, and how to share spectrum. However, this study does not address the concepts of architecture, task offloading, and optimization techniques.

Baktayan et al. [27] do a systematic mapping review of research on UAV-enabled MEC for task offloading, focusing on publications from 2019 to 2023. They do this to make research trends more straightforward, identify use case scenarios and architectures, group essential topics and techniques, determine which tasks can be offloaded, and summarize problems that still need to be solved and possible research paths. However, this research does not include channel access, task offloading taxonomy, optimization approaches, and UAV-enabled MEC applications.

Abrar et al. [28] examine the impact of computational resources and battery life when offloading tasks to nearby mobile MECs, focusing on architecture, communication, computational offloading, energy efficiency, and optimization. However, this study does not cover the optimization techniques and channel access in UAV-enabled MEC.

Ahmed et al. [29] explore the implementation of RIS-assisted UAV systems that focus on MEC functionalities by strengthening physical-layer security, lowering latency, improving energy efficiency, and expanding computing capacity. However, this study does not cover channel access, distributed task offloading, cost-based task offloading, and game-theory-based task offloading.

Table 2
Comparison of the existing surveys with our survey paper.

Reference	Architecture	Channel access	Offloading	Optimization	Cost	Energy-efficiency	Latency	Distributed task	Game theory	Feature	Limitations
Yazid et al. [20]	✓	×	✓	×	×	✓	✓	×	×	This study investigates UAV-enabled MEC for task offloading in IoT applications. It focuses on optimizing latency, energy efficiency, and security by incorporating DL and ML techniques.	It does not cover architecture, channel access, task offloading taxonomy, and optimization techniques.
Mkiramweni et al. [19]	✓	×	×	✓	×	✓	×	×	✓	This overview explores game theory methods for modeling and analyzing problems in wireless networks. It also provides a classification of these approaches.	It deals only with game theory methods.
Fatima et al. [21]	✓	×	×	×	×	✓	✓	×	×	It explores the integration of MEC with UAVs and 5G/B5G technologies, focusing on key performance indicators like latency, data rates, and connection density, as well as operational challenges including energy optimization, mobility management, and scheduling mechanisms.	It does not discuss channel access, task offloading taxonomy, and optimization techniques.
Huda et al. [22]	✓	×	✓	×	×	✓	×	×	×	This study specifically examines task offloading in UAV-enabled MEC systems, with a primary focus on optimizing service latency and energy consumption.	It does not explore channel access, all task offloading taxonomy, and optimization techniques.
Adnan et al. [23]	✓	×	✓	✓	×	✓	×	×	×	This work focuses on key aspects of UAV-enabled MEC, including system performance (such as latency and energy efficiency), resource management (including allocation and UAV trajectories), and security.	It does not discuss channel access, types of task offloading, cost-based, distributed task, and game-theory-based task offloading.
Mcenroe et al. [24]	×	✓	×	×	×	✓	×	×	×	This work presents a detailed analysis of AI applications in edge networks.	It does not discuss architecture, task offloading taxonomy, and optimization techniques.
Xia et al. [25]	✓	✓	✓	×	×	×	×	×	×	It focuses on resource management in UAV-enabled MEC, examining system architecture, key research directions, techniques, and performance indicators.	It does not cover task offloading, applications, and optimization methods.
Basharat et al. [26]	×	×	×	×	×	✓	✓	×	×	This survey comprehensively reviews resource optimization in UAV-assisted wireless networks, focusing on UAV placement, resource allocation, and spectrum sharing.	It does not discuss architecture, task offloading, and optimization techniques.
Baktayan et al. [27]	✓	×	✓	×	✓	✓	✓	×	×	This work provides an overview of the UAV-enabled MEC architecture, focusing on the techniques used for task offloading.	It does not focus on channel access, task offloading taxonomy, and optimization approaches.
Abrar et al. [28]	✓	✓	✓	✓	×	✓	×	×	×	It investigates the process by which computationally limited devices offload tasks to nearby MEC servers to conserve battery life.	It does not discuss the optimization techniques and channel access.
Ahmed et al. [29]	✓	×	×	✓	×	✓	✓	×	×	This paper offers a comprehensive overview of how RIS-assisted UAV systems enhance MEC capabilities, with key improvements in computational capacity, latency, energy efficiency, and physical-layer security.	It does not focus on channel access, distributed task offloading, cost-based task offloading, and game-theory-based task offloading.
Song et al. [30]	✓	×	✓	✓	×	×	×	×	×	It provides an overview of optimization strategies and ML techniques used to enhance the reliability and consistency of UAV-enabled MEC services.	It does not cover task offloading taxonomy, optimization methodologies, and channel access.
Maatauk et al. [31]	✓	×	✓	✓	×	×	×	×	×	This survey investigates how the integration of AI with UAVs can improve data offloading in MEC environments.	It does not focus on architecture, channel access, and any optimization processes.
Our survey	✓	✓	✓	✓	✓	✓	✓	✓	✓	Our survey examines key aspects of UAV-enabled MEC, including its architecture, channel access, and optimization approaches. We also address prevalent challenges and open issues, with a particular focus on offloading objectives such as latency reduction, energy and cost efficiency, and the methods used to achieve them, including game theory and other optimization strategies.	Null

Song et al. [30] investigate architecture, joint optimization, UAV deployment, task scheduling, load balancing, and machine learning-based optimization techniques in UAV-enabled mobile edge computing. However, this study does not analyze the job offloading taxonomy, optimization methodologies, or channel access.

Maatouk et al. [31] contend that integrating AI with UAVs can enhance data offloading in MEC settings. However, this study does not encompass the architecture's channel access or any optimization processes.

This study presents a comprehensive review of task offloading techniques, distinguishing it from other surveys on UAV-enabled MEC. It encompasses applications of UAV-enabled MEC, including communication channel access, architecture, and optimization approaches, as well as the challenges and open issues within these systems. Specifically, we address key concerns related to various offloading objectives, including cost-based, energy-efficient, latency-oriented, distributed tasks, game theory-based methods, and optimization strategies for task offloading.

Table 2 presents the comparison of the existing surveys with our survey paper.

3. UAV-enabled MEC architecture

UAVs play a crucial role in wireless communication frameworks [32, 33]. One notable architecture is the Predictive Acceleration Control Edge Device for 5G (PACED-5G), which represents an advanced edge computing approach. PACED-5G to offload computationally intensive high-level control algorithms to remote workstations, thereby minimizing processing delays [34]. The architecture aims to enhance service quality and efficient data processing by providing localized computing resources at the edge node, located near the UAV's data source, through a blockchain-based network structure [35]. Additionally, a master–slave architecture has been proposed, in which the UAV acts as the primary (master) device, communicating with a subordinate MEC server [36]. However, the UAV's functional role determines system architecture classification and directly influences the effectiveness and performance of the edge computing system. This role defines required capabilities and resources, impacts task offloading efficiency, and establishes the UAV's position in the network. Fig. 2 illustrates the various options for UAV-enabled MEC architectures.

The main role of a UAV as an MEC server is to handle computing tasks and serve as a flying edge server. It relies on a strong onboard MEC server as a key resource. Tasks offloaded from ground users or other devices are processed through its data flow. To deliver extra computing power for time-sensitive operations like real-time video analytics, a UAV can be used as a MEC platform over places such as stadiums or disaster areas. When acting as a connectivity provider, the UAV works as a wireless base station or access point. Here, computing power is either not present or less important. The UAV mainly provides radio access or communication resources, acting like an aerial cellular tower for the network. This shows how the UAV can switch between roles based on what the network needs. A UAV acts as a hybrid, integrating the capabilities of both a MEC server and a network access layer or relay. This has significant computational capabilities and robust communication transceivers. If it is a MEC server, it can perform computational activities; otherwise, it functions as a network access layer or relays tasks to other UAVs or ground servers, depending on load and task requirements. A UAV swarm in which certain UAVs perform computational work while others manage backhaul, or a singular UAV that adaptively chooses to execute a task or relay it depending on its present energy and CPU load. The UAV serves a relay function to augment communication lines. It emphasizes the enhancement of coverage extension and link quality, rather than computation. The primary role is to function as an amplifier or a decode-and-forward node. The data flow points between the task source and the computation destination reflect the data streams. A UAV functions as a device or user that generates computational work, acting as a consumer of edge computing services. Delegate its computationally hard activities to external resources. It functions as an end-user or client within the MEC network.

3.1. UAV as a MEC

A UAV acting as an MEC server mainly helps with running computer tasks. It works like a flying data center that gives basic computer power, storage, and handles tasks sent to it. Therefore, MEC improves cloud computing by positioning computational resources and data storage closer to the network's edge [37]. This strategy reduces latency, enhances processing speed, and boosts data throughput, which is crucial for time-sensitive applications. A primary advantage of UAV-based MEC is its ability to deploy on-demand computational resources rapidly in dynamic environments, ensuring reliable and efficient edge computing services [38]. Fig. 3 shows the role of the UAV as an MEC server within the UAV-enabled MEC architecture. The primary advantage of using UAVs as MEC in a UAV-Enabled MEC network is:

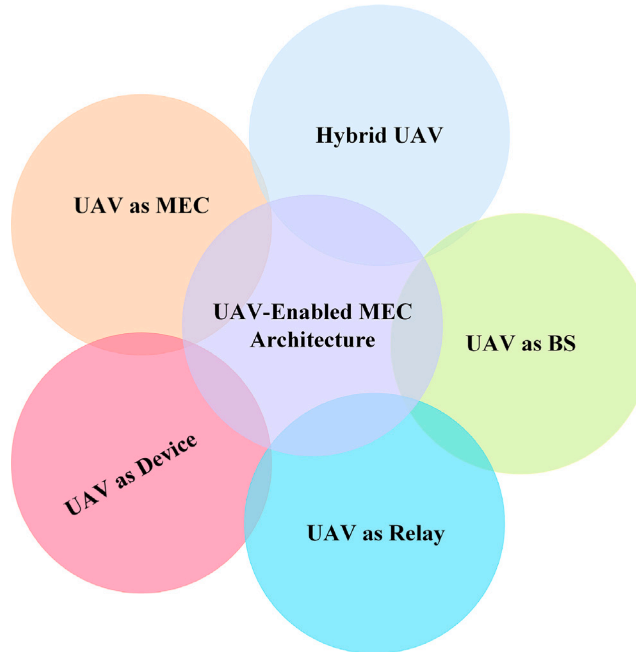

Fig. 2. UAV-enabled MEC possible architecture.

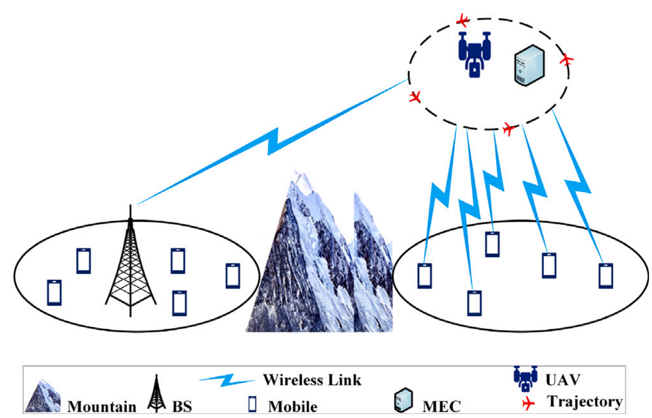

Fig. 3. UAV-enabled MEC architecture for UAV as MEC.

3.1.1. Computational service and flexibility

UAVs function as MEC servers, providing computational services to ground terminals [4]. Equipped with onboard computing resources, UAVs can be rapidly deployed to areas that require dynamic edge computing capabilities. Their versatility is especially beneficial in situations where traditional terrestrial infrastructure is either limited, damaged, or under high demand.

3.1.2. Energy efficiency

Energy plays a vital role in UAV-enabled MEC networks. Offloading computations to MEC servers equipped on UAVs reduces energy consumption for users and extends the battery life of IoT devices, sensors, UAVs, and mobile devices [39–42]. This is particularly beneficial for ground users handling computational tasks. In [43], a technique was proposed to deploy MEC-enabled UAVs to minimize total network energy consumption. Another optimization method aims to reduce completion times for fixed-wing UAVs with computational capabilities, considering the limited local power of IoT devices [44,45]. This allows UAVs to function as MEC servers and enhances the processing capabilities for ground users. Additionally, incorporating Non-Orthogonal Multiple Access (NOMA) enables multiple users to transmit simultaneously on the same frequency, eliminating the need for separate channels and reducing transmission time [46]. This integration further decreases energy consumption and improves system efficiency.

3.1.3. Load balancing and reduced backhaul congestion

Load balancing is essential for UAVs functioning as MEC servers to provide basic services to ground devices. For instance, Yang et al. [47] proposed a multi-UAV system equipped with MEC servers to enhance task processing for these devices. In their approach, they utilize differential evolution to distribute workloads among multiple UAVs, while Deep Reinforcement Learning (DRL) is used to manage task scheduling. By integrating these techniques, UAVs can execute tasks more efficiently. Moreover, processing tasks directly on UAVs minimizes the amount of raw data transmitted to the cloud, which helps alleviate backhaul issues, reducing costs and conserving bandwidth for network operators.

3.1.4. Resilience in disaster scenarios and decision-making

UAVs equipped with computing resources enhance resilience during disaster scenarios and support MEC services in these situations [48]. The integration of digital twin technology, a virtual replica of physical systems, offers additional advantages [49]. By integrating digital twins, which not only simulate network conditions but also empower decision-makers to improve computation offloading in uncertain environments [50], organizations can leverage both historical and real-time data to generate real-time predictions and optimize offloading decisions.

3.1.5. Low network latency and cost-effective

UAVs facilitate the scalable deployment of edge resources on demand. Many UAVs can work together as a group and share tasks [51], which is particularly beneficial during sudden demand, such as busy traffic or increased IoT data. By flying where nothing blocks their line of sight to people on the ground, UAVs boost signal and reliability in cities, forests, and regions with tall buildings [52]. Equipping UAVs with MEC servers allows for data processing closer to its source, eliminating the need for additional connections to central cloud servers [41]. This significantly reduces the delay to just milliseconds, which is essential for real-time applications, such as self-flying drones, and augments reliability, virtual reliability, and factory automation. Moreover, deploying UAVs in rural areas is often more cost-effective than constructing traditional cell towers [53].

3.2. UAV as a BS

A UAV can serve as a BS to enhance wireless communication and maintain user connectivity [54]. This innovative application is pivotal in telecommunications and network development. By utilizing UAVs as aerial BS, network coverage can be significantly improved, particularly in underserved areas or regions facing connectivity challenges. This technology expands the reach of communication networks and allows for rapid deployment in scenarios where ground infrastructure is limited, damaged, or inadequate. Fig. 4 illustrates the role of UAVs as BS in a UAV-enabled MEC wireless network architecture.

The backhaul is the part of the UAV that sends all of the collected user data traffic from the UAV's coverage area to the core network. There, it can be processed, stored, and accessed from the internet. Even though it has strong radio access capabilities, the UAV cannot serve as an access point effectively without a reliable, high-capacity backhaul. Therefore, to increase a ground-based cellular network's total capacity by using a UAV aerial base station or relay with a free-space optical backhaul, while specifically taking into consideration how bad weather, especially fog, affects backhaul dependability [55]. Focusing on evaluating and enhancing network coverage probability, analyze the effectiveness of the integrated access and backhaul architecture in dynamic aerial-terrestrial networks, wherein mobile aerial base stations are wirelessly backhauled by fixed ground base stations [56]. One of the main ways to simulate the random spatial distribution of nodes and get theoretical formulas for coverage probability and handover rate that take into account the effects of GBS density and ABS mobility is to use a stochastic-geometry-based analytical framework.

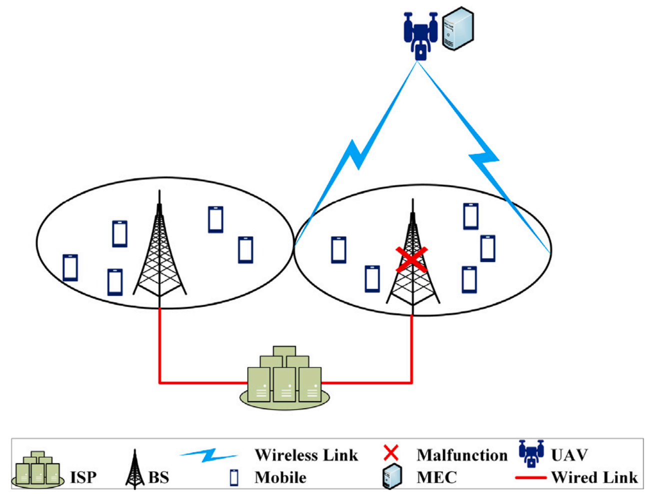

Fig. 4. UAV-enabled MEC architecture for UAV as BS.

The basic advantages of UAV as a BS are explained in detail below.

3.2.1. On-demand deployment

The use of UAVs as mobile BS can significantly enhance user mobility by predicting and monitoring user locations, ultimately improving energy efficiency. In disaster-stricken areas, UAVs can operate as small BS or serve as edge relay nodes, effectively addressing complex deployment challenges [57]. They can be deployed rapidly to respond to sudden demand in various locations such as concerts, emergencies, or areas lacking fixed infrastructure.

3.2.2. Increase network capacity and coverage

The integration of UAVs as aerial BSs in a Multiple-Input Multiple-Output (MIMO) architecture can dramatically increase network capacity and coverage for terrestrial users [2]. This strategy allows network operators to enhance efficiency, expand coverage, and boost uplink communication performance in congested wireless environments. By functioning as flying BSs, UAVs provide reliable network and capacity for both uplink and downlink communication for ground users, especially in emergencies [58].

3.2.3. Energy efficiency for ground users

Energy efficiency is important for both UAVs and mobile devices. In the case of mobile devices, techniques such as resource partitioning and bit allocation can significantly reduce energy consumption [59]. The deployment and movement patterns of UAVs also influence the energy requirement of ground users as tasks are completed [60]. When UAVs serve as BSs, they enable IoT devices to offload demanding tasks to their onboard servers, thereby saving energy and extending battery life.

3.2.4. Integration with B5G/6G and AI

UAVs serving as BSs enhance B5G/6G beamforming [61] and support massive MIMO capabilities. Onboard AI enables real-time analytics, including traffic prediction and anomaly detection.

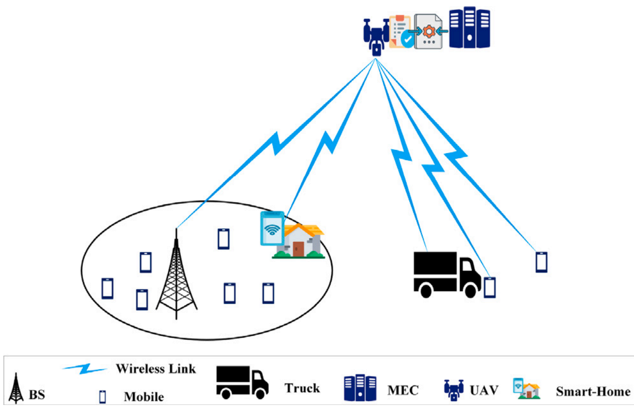

Fig. 5. UAV-enabled MEC architecture for UAV-Hybrid.

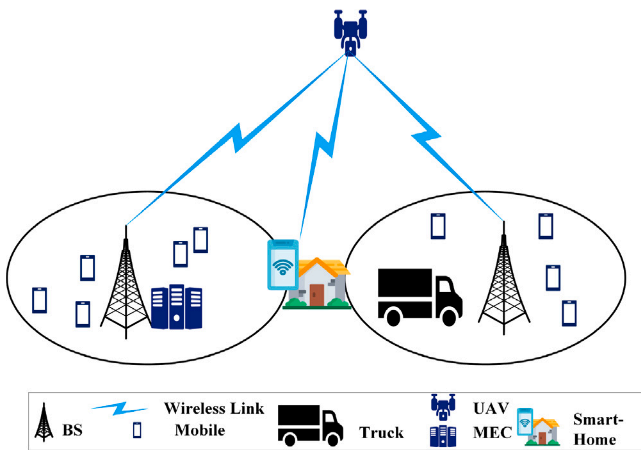

Fig. 6. UAV-enabled MEC architecture for UAV as a relay.

3.3. Hybrid-UAV

Hybrid UAVs possess both computation and communication capabilities, enabling them to function as MEC nodes as well as aerial BSs. This dual functionality allows UAVs to process data locally while also providing network connectivity. Furthermore, UAVs can collaborate with one another to perform computational tasks within the UAV-enabled MEC network [62]. Fig. 5 illustrates the role of hybrid UAV services in the architecture of the UAV-enabled MEC wireless network. UAVs are utilized to support IoT devices with limited resources in a hybrid coded edge computing network [63]. This network implements a hybrid approach for managing computational tasks in wireless networks [64]. This strategy integrates local computation, edge offloading, and wireless power transfer. The key advantage of a hybrid UAV is its ability to leverage the benefits of both MEC and BS functionalities.

3.4. UAV as a relay

Deploying UAVs as relays significantly improves communication networks by expanding coverage and connecting distant nodes. This capability is particularly beneficial in areas where physical barriers obstruct direct connections or when distances surpass the effective range of terrestrial transmitters, as illustrated in Fig. 6.

The basic advantages of utilizing UAVs as relays in UAV-enabled MEC networks include:

3.4.1. Coverage extension

Devices located outside BS's territorial boundaries were connected through a UAV-assisted device-to-device MEC multi-relay system [38]. This system employs energy harvesting to minimize overall work completion time and optimize the simultaneous allocation of various resources. Multiple UAVs serve as intermediate relays between user equipment and the MEC server, effectively addressing quality of experience and battery life constraints [3]. These UAV relays dynamically reposition themselves to extend coverage to underserved or obstructed areas, such as rural zones and dense urban environments. By acting as intermediate nodes, they link ground users to MEC servers or terrestrial BS, ensuring seamless service continuity.

3.4.2. Line-of-Sight (LoS) connectivity

One of the primary advantages of utilizing a UAV as a relay is its ability to maintain designated altitudes and navigate optimal routes. This capability ensures reliable LoS communications while minimizing signal obstructions [52]. The LoS characteristic significantly reduces path loss compared to terrestrial relays, which enhances throughput for bandwidth-intensive MEC applications such as video analytics. These direct connections help mitigate signal blockage, lower latency, enable higher data rates, enhance signal quality, and increase security in wireless communications [65].

3.4.3. Multi-hop routing for minimizing latency

UAV relays establish shorter links between users and MEC servers using multi-hop routing [66,67]. Effective relay selection forwards data through the most optimal UAVs, which enhances task offloading and lowers end-to-end latency. This reduction in latency is particularly important for delay-sensitive uses such as autonomous driving and telemedicine.

3.4.4. Cost-effective

Integrating DL algorithms that learn from large datasets, ML focused on pattern recognition and decision making, and Software-defined Networking (SDN) for a network management approach, enables automated control with UAV-assisted offloading. This approach increases cost efficiency in vehicle computational offloading. In particular, the SDN approach [68] enables the UAV to relay data between the vehicle and MEC, thereby placing computation near users. It reduces server latency and decreases computing task costs. Moreover, in remote areas, UAV relays offer economical MEC connectivity for applications such as precision agriculture and telehealth.

3.4.5. Load balancing and traffic optimization

To effectively reduce network congestion, UAV relays play an essential role in dividing traffic among several MEC servers or BS [69]. This technique is enhanced by ML algorithms that optimize routes based on real-time demand. For instance, UAV relays can balance video streaming traffic across edge servers during a sports event.

3.4.6. Energy efficiency for IoT devices

While solutions for energy consumption are still being developed, using UAVs for computation offloading can significantly improve overall energy efficiency [70]. This improvement focuses on two key areas: optimizing transmit power allocation and improving the UAVs' flight paths through trajectory optimization. By integrating these approaches, minimizing the wireless transmission distances for ground users through UAV-assisted relays enables IoT devices to reduce their energy consumption. As a result, rather than transmitting data directly to distant BSs, devices can send their data to UAV relays that are positioned closer to them.

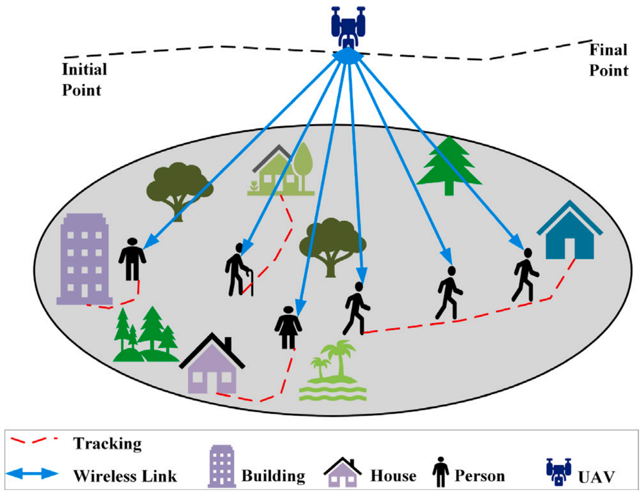

Fig. 7. UAV-enabled MEC architecture for UAV as tracking devices.

3.5. UAV as a device

The UAV acts as a client or user, rather than a service provider. These UAVs have limited processing capabilities and typically offload resource-intensive tasks, such as path planning and image recognition, to a powerful MEC server. UAVs can be equipped with various sensors and gadgets to allow them to perform multiple tasks simultaneously or switch between functions as needed. Their adaptability makes them valuable across a range of industries. Fig. 7 shows the UAV's role as a device in a UAV-enabled MEC wireless network architecture.

The primary advantages of using a UAV as a device are outlined below.

3.5.1. Tracking objects

A UAV-aided target tracking mechanism was proposed by Deng et al. [71], which utilizes UAVs to track objects by integrating an MEC server with a ML algorithm [72]. UAVs can be equipped with specialized hardware and thermal cameras to perform specific tasks, such as environmental monitoring or healthcare delivery.

3.5.2. Enhance connectivity and scalability

Incorporating UAVs into networks enables rapid resource allocation, reducing both costs and time compared to constructing permanent infrastructure. UAVs improve communication coverage in areas with weak signals, providing more individuals with access to essential services. For example, deploying additional UAVs can help manage increased data traffic.

3.5.3. Support ubiquitous computing

UAVs play a key role in industrial and scientific environments by improving robotic communication, increasing productivity, and reducing the risk of manufacturing accidents. In the mining sector, UAVs are valuable for 3D mapping, public safety, and improving the management of operations. UAV-assisted B5G networks and Industry 4.0 and 5.0 technologies address data processing and storage issues in IoT systems with limited resources [73]. Additionally, ubiquitous computing in the sky contributes to improved service quality and reduced energy consumption.

3.5.4. Mobility and flexibility

UAVs can dynamically reposition themselves to optimal locations, ensuring they stay close to users or IoT devices. This mobility enhances service quality in crowded events, disaster zones, and remote areas lacking static infrastructure. UAVs can identify the best offloading strategy and dynamically chart their paths, thereby computing, caching, and offloading decisions across the designated search region [74].

4. Communication channels access

Communication channel access can be classified into several categories, including Time Division Multiple Access (TDMA), Frequency Division Multiple Access (FDMA), Code Division Multiple Access (CDMA), Orthogonal Frequency Division Multiple Access (OFDMA), Non-Orthogonal Multiple Access (NOMA), and One-to-One.

Chen et al. [75] analyze multiple access schemes in IRS-aided wireless powered MEC systems and demonstrate that the performance of TDMA and NOMA strongly depends on the system's degree of freedom. Dai et al. [76] propose an energy-efficient and secure computation offloading scheme designed for marine public safety. They combine UAVs with NOMA/FDMA and develop a layered optimization framework. Ahmad et al. [77] introduce an optimization framework for multi-UAV communications using NOMA, focusing on user-to-drone association and power allocation. The objective of this proposed framework is to maximize spectral efficiency while addressing the challenges related to mobility and co-channel interference. It involves practical constraints, mixed-integer optimization, and provides quantitative results for OMA baselines. Lei et al. [78] target secure and efficient task offloading under UAV-MEC networks and use deep reinforcement learning and Deep Deterministic Policy Gradient (DDPG). Their proposed approach employs NOMA to achieve high spectral efficiency and DRL to support dynamic planning. The proposed DDPG can resolve the Three-Dimensional (3-D) flight problem in imperfect parameters.

These strategies are vital for ensuring smooth, interference-free uplink (from device to UAV) and downlink (from UAV to device) communication within UAV-MEC networks. Ultimately, these approaches enable highly efficient computation offloading, where computational tasks are sent from mobile users and UAVs. The strategic deployment of UAVs, supported by robust LoS wireless links and advanced access strategies, has demonstrated greater efficiency compared to traditional land-based MEC networks.

4.1. TDMA

TDMA enables multiple devices to share a single frequency channel by dividing the signal into distinct time slots [79]. This separation of time slots ensures predictable communication and minimizes the risk of collisions.

Non-convex problem: involves decision variables related to a system, UAV flight path, scheduling, and resource allocation. These aspects are complex, coupled, and non-linear, with each element playing a distinct yet interdependent role. The UAV's flight path affects which users can be reached, while scheduling determines when and how resources are assigned to users. Additionally, resource allocation controls bandwidth, computation resources, and task offloading [80]. Since each variable influences and is influenced by the others, optimizing them jointly is essential for achieving the best results [81].

To address this issue, Hu et al. [60] proposed a framework to optimize energy use in a multi-user aerial MEC system, where servers mounted on UAVs provide computing resources. Their approach jointly optimizes UAV positioning, TDMA-based time-slot allocation, and task partitioning between ground users and UAV-mounted servers. The problem is non-convex because offloading time and task variables are coupled. To address this, they use convex optimization with Karush-Kuhn–Tucker (KKT) conditions and a bisection search for the Lagrangian multiplier (μ) to minimize total user energy consumption.

4.2. FDMA

FDMA divides the available bandwidth into distinct, non-overlapping frequency bands. Each user is allocated a specific band for the duration of their communication session. This approach is widely adopted due to its straightforward and efficient resource allocation [82].

Non-convex, non-linear, and mixed-variable: To address this issue, Wang et al. [83] introduced a framework for deploying and managing multiple UAVs as edge servers in a MEC system, which supports dynamic computation tasks from many mobile users. The system uses FDMA to divide bandwidth equally among UAVs, making it easier for users to connect. It leads to an optimization problem that is both non-convex and nonlinear, with mixed-variable constraints from resource allocation and scheduling. To address these issues, the authors implemented a two-layer optimization framework along with a greedy algorithm to schedule tasks and allocate resources, aiming to reduce total energy consumption in the multi-UAV MEC system while serving a large number of users.

Non-convex and NP-hard: A non-deterministic polynomial-time hard (NP-hard) problem is defined as being at least as challenging as the most difficult problems in NP. In the context of UAV-MEC, this classification significantly influences the selection of practical solution methods. The NP-hardness of the problem results from the integration of discrete decision variables with continuous optimization components [84]. To address this issue, Diao et al. [85] proposed a joint optimization framework that integrates offloading and UAV trajectory planning with FDMA. Their solution addresses non-convex, NP-hard problems caused by integer variables and non-linear constraints. They employ Successive Convex Approximation (SCA), aiming for Min-Max fairness in energy consumption for both users and UAVs, which helps extend system life and enhances user satisfaction.

4.3. CDMA

CDMA is a channel access method that allows multiple transmitters to send information simultaneously over a single frequency channel. It is achieved by assigning a unique, orthogonal spreading code to each user. CDMA is not just an alternative; it is a necessary evolution that enables communication systems to efficiently support large numbers of users where traditional time-scheduled systems fall short [86].

Non-convex and NP-hard: To address this issue, Ning et al. [87] introduced a distributed framework that helps multiple users and UAV-mounted MEC servers in making better decisions regarding offloading computation and deployment of servers. Their system uses CDMA technology for communication between user devices and UAVs. The problem they address is NP-hard. To address this issue, the authors model user interactions as stochastic games and apply learning algorithms to inform decision-making. The proposed system aims to reduce overall computation costs, such as latency and energy consumption, in a setting where users generate tasks at different times and rates.

4.4. OFDMA

OFDMA is a digital multi-carrier modulation scheme and a multiple access method. It enables simultaneous data transmission across multiple frequency channels, thereby minimizing interference between edge servers and mobile devices [88]. Besides, it is a fundamental technology behind modern broadband wireless systems like Fourth Generation Long-Term Evolution (4G LTE) and 5G. The ability to dynamically reassign fine-grained subcarriers and power resources makes it possible to develop a low-complexity, high-performance algorithm that maximizes fairness (minimum rate) in a UAV network [89,90].

Non-convex and NP-hard: To address this issue, Mei et al. [91] proposed a joint framework for optimizing both trajectory and resource allocation in a UAV-enabled edge-cloud system using virtualized Mobile Clones (MCs). Specifically, the proposed system first applies OFDMA for downlink communication between the air-to-ground terminal. The approach sequentially leverages Block Coordinate Descent (BCD), convex optimization, SCA, and Lagrange duality with the Sub-Gradient method to address the NP-hard, non-convex problem. Ultimately, the main goal is to minimize UAV total energy consumption, including propulsion and service-related energy, while satisfying users' task latency requirements.

4.5. NOMA

NOMA is a multiple-access technique for wireless communication that enables multiple users to share the same time and frequency resources simultaneously. Therefore, NOMA has the potential to be a key enabling technology for efficient and scalable IoT communication infrastructure [92]. UAV-enabled relaying, when integrated with NOMA, allows multiple users to share the same spectrum using different power levels. It enhances MEC by processing tasks closer to IoT devices at the edge of the network. These tasks are forwarded to an access point using two main methods:

- Decode-and-forward: In this method, the UAV decodes the data before re-transmitting it.
- Amplify-and-forward: The UAV amplifies the received signals before re-transmission.

4.5.1. Non-convex and NP-hard

To address this issue, Guo et al. [70] proposed a framework that optimizes both trajectory and computation offloading. In their approach, the UAV serves as a relay between mobile users and the BS, and uses NOMA to enhance spectral efficiency. To address the non-convex and NP-hard optimization challenge, the authors employed the SCA method and implemented a two-stage iterative algorithm. Their main goal is to reduce total user delay, considering the UAV energy limits and quality of service requirements for users.

4.5.2. Non-convex

To address this issue, Zhang et al. [93] proposed a flexible framework for UAVs using MEC. Their system integrates FDMA for UAV communication with NOMA for links between users and UAVs. The non-convexity mainly comes from the constraint linking transmit power and UAV trajectories in the NOMA offloading data rate expression. The authors employed SCA, quadratic approximation, and an alternating optimization algorithm. The main goal is to minimize the weighted total energy consumption of the UAV-NOMA-MEC system.

4.5.3. Successful computation probability

The primary focus of successful computational probability is to assess and maximize the likelihood that a computational task will be completed on time. This approach accounts for uncertainties and random events that may lead to task failure. Rather than merely focusing on reducing energy consumption or delays, the goal is to ensure that the probability of success meets or exceeds a specified reliability threshold [94]. To address this issue, Nguyen et al. [95] proposed a system in which a UAV serves as a relay for a cluster of resource-constrained IoT devices, enabling them to offload computation tasks to two ground-based MEC Access Points (APs). The key result is an analytical expression for the Successful Computation Probability (SCP), the probability that tasks finish within a set deadline using stochastic geometry and probability theory. Rather than optimizing resource allocation, the study's main focus is the derivation and evaluation of SCP under the proposed system with downlink NOMA in the relay-to-APs phase.

4.5.4. Mixed-integer nonlinear programming problem

A combination of elements of both mixed-integer and nonlinear programming. In context, mixed-integer variables can be either continuous, such as transmission power, UAV trajectory, and CPU frequency, or discrete, including user association, offloading decisions, and UAV selection [96]. The problem becomes nonlinear when the objective or constraints use nonlinear functions of these variables. To address this issue, Farha et al. [97] proposed a framework to optimize task offloading in multi-UAV-enabled MEC systems. They utilize the spectral efficiency of NOMA to maximize the total data offloaded from all IoT devices during a set service period. The proposed model is a

Table 3
Summary of channel access mechanisms in UAV-enabled MEC systems.

Channel access	Reference	Problem	Technique	Feature
TDMA	Hu et al. [60]	Non-convex	Karush-Kuhn–Tucker and using a bisection search	Minimizing the energy consumed by the ground users and ensuring successful task computation.
FDMA	Wang et al. [83]	Non-convex, nonlinear, and mixed-variable	Two-layer optimization with a greedy algorithm	Minimize system energy consumption while ensuring efficient task execution for numerous mobile users.
	Diao et al. [85]	Non-convex and NP-hard	Successive convex approximation	Ensuring fair energy consumption for both user equipment and UAVs.
CDMA	Ning et al. [87]	Non-convex and NP-hard	Stochastic games and learning algorithms	Reducing computation costs across the entire system in dynamic environments.
OFDMA	Mei et al. [91]	NP-hard and non-convex	Block coordinate descent, convex optimization, successive convex approximation, and Lagrange duality with the sub-gradient	Minimization of energy consumption in the ground terminals and the UAV.
	Guo et al. [70]	Non-convex and NP-hard	Successive convex approximation and a Two-stage iterative algorithm	Minimized the total delay in the network.
	Zhang et al. [93]	Non-convex	SCA, quadratic approximation, Successive convex approximation, quadratic approximation, and alternating optimization algorithm	Minimize energy usage and optimize resource management.
NOMA	Nguyen et al. [95]	Successful computation probability	Stochastic geometry and probability theory	UAV relay is responsible for forwarding tasks from an edge cluster of IDs to APs.
	Farha et al. [97]	Mixed-integer non-linear Programming	Block coordinate descent and successive convex approximation	Optimizing efficiency and minimizing latency.
	Xu et al. [98]		Concave-Convex Procedure and grid search	Increase the overall computation capability of the UAV.
One-to-One	Hua et al. [101]	Mixed-integer non-convex optimization	Karush-Kuhn–Tucker and successive convex approximation	Energy-efficient scheme for computational task offloading.

Mixed-Integer Non-Linear Programming (MINLP) problem and is solved with BCD and SCA methods. Their main objective is to maximize the number of bits offloaded by jointly optimizing UAV-user association, UAV transmit power, and UAV trajectories under energy and quality of service constraints. Xu et al. [98] introduced a RIS for a UAV-MEC system. Their approach employed NOMA to enhance the computing power of UAVs, allowing them to offload tasks to several ground APs and thereby better manage many connections. The authors identify the core challenge as a MINLP problem with non-convex constraints. To address this problem, they utilize the concave-convex procedure (CCCP) and grid search. They aim to enhance the UAV's computing capacity through joint optimization of communication, computation, RIS, and UAV placement.

4.6. One-to-one

4.6.1. Mixed-integer non-convex optimization problem

UAV-enabled MEC involves both mixed-integer variables and non-convex structures. Solving these types of problems can handle discrete decision variables and effectively address non-convexity. This often involves integrating integer programming with advanced nonconvex optimization methods [99,100]. To address this issue, Hua et al. [101] proposed using a single UAV to act as a flying BS that offloads and processes users' computational tasks. Specifically, their main contribution is the one-to-one access scheme, where only one user is served at a time. To tackle this challenge, the authors set up a mixed-integer non-convex optimization problem that includes both integer and continuous variables. To solve this, they applied KKT conditions for constrained optimization, used SCA to break the problem into convex sub-problems, and developed an iterative algorithm. The primary objective throughout is to reduce the total energy consumption of all ground users.

Table 3 presents a summary of the channel access mechanism in the UAV-enabled MEC system.

5. UAV-enabled MEC task offloading

UAVs are attractive because they are flexible, easy to deploy, cost-effective, and compact, allowing them to serve as edge servers, creating UAV-enhanced MEC servers. These servers offer users mobile edge services and on-demand communication and computation resources. They are especially useful where fixed terrestrial MEC networks are either inaccessible or cannot be quickly set up, and they can also be invaluable in situations where disasters have damaged existing MEC systems [102]. To improve the networks' effectiveness, two strategies have been proposed: optimal power allocation and deployment, and distributed resource allocation and deployment [103]. These strategies aim to identify globally optimal solutions and achieve a better local strategy. For task offloading, Federated Learning (FL) can support task prediction, UAV position design, and joint resource allocation across devices [104].

A framework [105] proposed a collaborative optimization of discrete offloading selections and continuous resource allocation in dynamic multi-user, multi-server mobile edge computing environments. The main goal is to lower the system's total cost, which is a weighted sum of latency and energy use. This is done by accounting for how users move around and how channel conditions change over time. The authors make a DRL solution by improving the Twin Delayed Deep Deterministic Policy Gradient algorithm. This new algorithm uses two critic networks and a delayed update mechanism to prevent Q-value overestimation.

A multi-task-oriented computational offloading was proposed [106], with the primary objective of minimizing task completion time and energy consumption. A two-stage mechanism based on an edge-node recommendation model was implemented in a cloud–edge-end architecture to achieve this. The first step in this model is to narrow the optimization search space by filtering and suggesting the best edge nodes based on the user's location and available computing resources. They make a chemical reaction optimization-based algorithm for the core optimization. This algorithm treats decisions about offloading like molecular structures and uses bio-inspired operators.

A technique employed to tackle dependent task offloading in edge computing contexts, where various interrelated subtasks vie for scarce computational and communicative resources in both single-user and multi-user situations [107]. The main goal is to shorten the time required to complete all tasks by implementing an intelligent scheduling system. The suggested method, dependent-task offloading DRL, uses

Table 4
Criteria used to categorize the task offloading mechanism.

Criteria	Categories	Features
Optimization objective	Latency, Energy, Joint, Throughput, QoS, and Cost	Focusing on the aim or object to be improved or enhanced.
Offloaded coordination style	Central, Distributed, Hierarchical, and Learning-based	Focusing on the offloading decision-making.
Offloading destination	Local, UAV-MEC, Ground-based MEC, and Hybrid	Focusing on the task offloaded to.
Offloading granularity	Binary and Partial (task partitioning)	Focusing on the portion of the task that is offloaded.
Task Execution	Local, Partial, and Full offloaded	Focusing on the location of the task execution.

directed acyclic graphs to show how tasks depend on each other and a graph attention network trained without supervision to encode state representations structured like graphs.

Improving wireless connectivity, computational performance, and energy reliability for mobile devices in 5G and future networks [108], depends on real-time status updates for UAVs through computation offloading to edge servers. Recent techniques use DRL mechanisms to achieve this, recognizing the demands of the information age. UAV-assisted MEC also uses a digital twin technology to improve the matching of computational offloading tasks [109]. Building on these ideas, two levels of UAV-assisted MEC offloading and a strategy called Flexible Hybrid Subtask Offloading (FHSO) are designed to make aerial communications more efficient in computing and communication [110]. During optimization, a UAV decides whether to offload processing tasks to an edge server or handle them locally. In particular, UAV-enabled MEC task offloading uses three main models, namely:

- The Local Computing Model executes tasks on mobile devices.
- The Computation Task Offloading Model allows users to send their tasks to a MEC server, which can be located on a UAV or at a base station, for processing.
- The UAV Hovering Model facilitates task uploads and execution at a fixed location for a specified duration.

Table 4 is a systematic taxonomic instrument for researchers and practitioners to compare and contrast task offloading strategies in UAV-MEC systems. Each criterion provides a distinct viewpoint on the rationale for offloading (optimization target), the coordination involved, the destination of tasks, the volume of offloading, and the location of execution. The survey prioritizes execution level as its primary classification criterion, while it offers a more comprehensive framework for a holistic knowledge of offloading processes.

Fig. 8 presents a decision flowchart outlining the process of computational offloading for task offloading in the UAV-enabled MEC system [28]. Additionally, it is generally advised that jobs be transferred from manually controlled systems to autonomous ones in MEC systems enabled by UAVs and ground users. This approach enhances efficiency, flexibility, and safety.

5.1. Full offloading

It refers to the process in which UAVs transfer all computational tasks, including those from ground users, to MEC servers instead of processing them locally [8,9]. This method utilizes the superior computational capabilities of MEC servers to handle complex tasks that demand substantial resources. Due to size, weight, and power constraints, UAVs frequently cannot process such tasks independently.

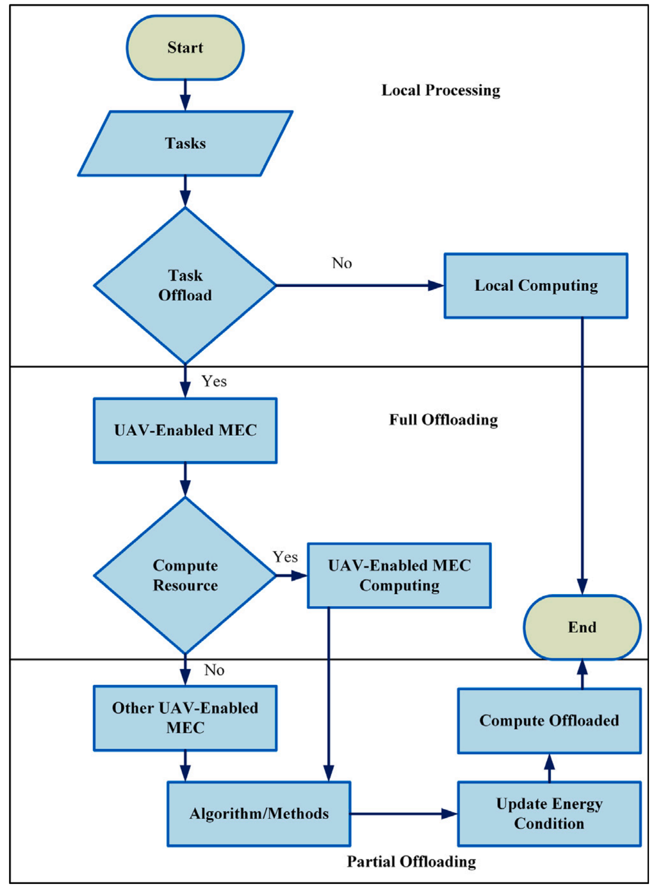

Fig. 8. Decision flowchart of computational offloading mechanism.

5.1.1. Non-convex mixed-integer programming

To address this issue, El Haber et al. [111] introduced a system that enables low-latency, highly reliable computation offloading for demanding applications such as autonomous driving and smart manufacturing. The proposed system deploys UAVs equipped with edge servers, or “cloudlets”, to create a flexible airborne computing infrastructure. UAV-mounted cloudlets fail more often than ground servers. To address this, SCA-based iterative methods were used, and the same subtask was performed on multiple UAVs to ensure reliability. The aim of the proposed framework for maximize the number of users served or tasks.

5.1.2. Mixed-integer nonlinear programming (MINLP)

To address this issue, Bao et al. [112] employed K-means clustering to group similar tasks and the penalty method to solve the complex problem. These strategies enable UAVs to handle offloaded tasks more efficiently and optimize resource usage. Consequently, UAVs can complete tasks more simply and speed up processing. As a result, UAVs spend less time hovering, finish tasks faster, save energy, and work more reliably in MEC networks. The deployment of UAVs also contributes significantly to reducing job offload time. Sun et al. [113] applied a 3-D multi-UAV deployment along an SCA approach to minimize job completion time to solve the MINLP problem. Ning et al. [114] proposed a method for joint optimization of UAV flight trajectory and job scheduling in a 5G-enabled UAV communication system. They aim to optimize the overall system throughput. Specifically, they accomplish this by grouping users into geographically adjacent communities inside the UAV-to-community offloading structure, which helps to increase throughput. Furthermore, the intra-community scheduling sub-problem is part of the MINLP challenge and uses a dynamic task admission algorithm. This algorithm optimizes task admission by considering resource allocation and task deadline constraints, thereby further improving throughput. Liao et al. [115] employed a heuristic algorithm, a Lagrangian multiplier method using KKT conditions, and an SCA-based algorithm to solve the MINLP issue.

5.1.3. Generalized assignment problem

The generalized assignment problem involves assigning specific objectives to various agents [47]. In UAV contexts, this problem is particularly relevant for allocating computational tasks from ground users to UAVs. When making these assignments, several factors must be considered, such as computational resources, wireless channel conditions, and, in some cases, flight paths. The main goal is to minimize energy use or reduce delay. To address this issue, Chunxiao et al. [47] designed a system in which several UAVs with MEC servers handle ground tasks. They employ differential evolution to ensure tasks are matched to available resources and prevent resource overload. Additionally, DRL is used to ensure that each UAV completes its tasks on time, thereby maximizing system throughput. By combining these approaches, the system efficiently shares resources and tasks, avoiding bottlenecks and increasing the number of completed tasks across the UAV network.

5.1.4. Multi-agent offloading problem

This problem goes beyond the basic assignment of task-to-UAV. Multiple autonomous UAVs (agents) must cooperatively manage a continuous stream of computational tasks from ground users [116]. There is no centralized decision-maker; instead, each UAV uses only partial or local information to make decisions and must coordinate with others to achieve a shared system objective. To address this challenge, Wu et al. [117] introduced a method for efficient task assignment to UAVs in edge computing, a capability critical for latency-sensitive applications like autonomous vehicles and smart cities. Their approach minimizes user wait times by optimizing the matching between users, UAVs, and network links, even under fluctuating network conditions. The core of their solution is the Combinatorial Bandit Upper Confidence Bound (CB-UCB) method, which enhances an existing learning algorithm by incorporating task-specific information to make more intelligent assignment decisions. By rapidly adapting to real-time network dynamics, CB-UCB enables faster and more accurate matching, thereby directly improving system responsiveness and reducing latency. Consequently, this method enhances the overall reliability and efficiency of edge computing systems, enabling them to support a larger number of users.

5.1.5. Non-convex

To address this challenge, Zhou et al. [118] proposed a novel approach in which a single UAV acts as a hybrid model. It serves as a wireless power ground for users and also provides MEC services for their computation tasks. The core objective is to minimize the total energy consumption of the UAV. The authors solve it by decomposing it into two sub-problems and proposing an efficient iterative algorithm based on alternating optimization and SCA. Zeng et al. [119] address non-convexity by first employing a Stackelberg game architecture to model leader-follower interactions. They then use Lyapunov optimization theory to handle queue stability. Following this, they apply Lagrangian duality theory and alternative optimization to solve the resulting optimization problems. Finally, the SCA method is applied to refine the non-convex objectives. Together, these sequential methods minimize waiting delay for user equipment and control the UAV's energy consumption as it serves a large area. The UAV is equipped with both an MEC server and an energy transmitter.

5.1.6. Optimal offloading problem

The optimal offloading requires strategies for task placement, resource allocation, and UAV movement to meet system goals within specified limits [31]. Since finding a global optimum is unrealistic, iterative, learning-based methods are used to obtain efficient, near-optimal solutions. To address this issue, Cao et al. [120] proposed a UAV inspection system for wind farms that uses MEC and a Space-Air-Ground Integrated Network (SAGIN) to speed up and coordinate inspections in windy conditions. Their main contribution is a two-step process that integrates route planning and decision-making, using an algorithm to help UAVs decide when to offload tasks. MEC enables UAVs to process data locally, reducing delays, while SAGIN connects satellites, UAVs, and ground networks to share information efficiently.

5.1.7. Mixed discrete and non-convex

To address this issue, Qian et al. [121] developed a two-layered algorithm that integrates a top-layer DRL approach with a lower-layer Lagrangian multiplier method to tackle the issue of mixed discrete and non-convex optimization. Their proposed work focuses on integrating Maritime-IoT (M-IoT) technology with UAV and surface vehicles. The goal is to enhance energy efficiency and workload computation in UAV-assisted M-IoT networks. The authors present a comprehensive joint optimization framework to address energy consumption, accompanied by an efficient algorithm design.

5.1.8. Optimal association scheme problem

The optimal association scheme problem focuses on assigning each ground user, or their computational tasks, to a specific UAV server in a network with multiple UAVs [122]. The aim is to match users to UAVs in a way that maximizes the overall performance of the system. Han et al. [123] proposed an optimal association scheme by relying on the optimal transport theory to tackle the user association sub-problem. In this approach, UAV deployment is optimized using a classical Particle Swarm Optimization (PSO) algorithm. The goal is to minimize the average task delay of a UAV-aid MEC network, which includes both terrestrial BSs and UAVs coexisting with different capabilities.

Table 5 provides a summary of full task offloading techniques.

5.2. Partial offloading

It allows UAVs to perform specific computational tasks while delegating others, such as data analytics or image processing, to a nearby MEC server for processing [124]. For instance, a UAV might manage obstacle detection independently but send high-resolution video analysis to the MEC server. By collaborating this way, the MEC server and UAV can distribute the workload by sorting tasks according to their processing needs.

5.2.1. Non-convex

Zhou et al. [125] proposed a joint algorithm for positioning UAV and task offloading to maximize computation rate. They mitigated the effects of non-convexity in optimizing UAV position, time allocation for wireless energy and information transfer, and task offloading. Ji et al. [126] developed a block alternating descent approach to solving the non-convex problem. They applied a one-UAV computing resource model for MEC task offloading, with the goal of minimizing network energy consumption. Bai et al. [127] address issues related to user-assisted real-time task scheduling in a multi-UAV edge-cloud computing system. They first identified these challenges and then proposed a collaborative offloading scheme to minimize the delays. Their method utilizes optimization, Lyapunov optimization, and convex approximation to derive real-time task-offloading decisions based on system state information and workload distribution. Xia et al. [128] consider the task processing delay minimization problem with coordinated UAVs in an MEC network. The authors design a two-layer optimization algorithm, which is capable of achieving near-optimal UAV deployment

Table 5
The summary of the full task offloading techniques.

Problem	Reference	Technique	Feature
Generalized assignment	Yang et al. [47]	DRL	The proposed approach maximizes UAV task execution efficiency through load balancing.
Non-convex mixed-integer programming	El et al. [111]	SCA-based iterative algorithm	It focuses on maximizing the number of tasks served while adhering to strict latency and reliability constraints.
MINLP	Bao et al. [112]	K-means clustering and penalty	By using cooperative computation and effective cache scheduling, endurance time is significantly enhanced, resulting in significant savings.
	Sun et al. [113]	Successive convex approximations	Minimize the UAV's total time to complete the offload task.
	Ning et al. [114]	Community-based latency approximation algorithm	This approach optimizes the efficiency of task and resource utilization and maximizes system throughput.
	Liao et al. [115]	Heuristic, Lagrangian with Karush–Kuhn–Tucker, and SCA-based algorithm	The proposed method optimizes offloading decisions for effective energy consumption management.
Multi-agent offloading	Wu et al. [117]	Combinatorial bandit classical upper confidence bound algorithm	In that approach, a UAV is deployed as a macro base station to minimize utility cost.
Non-convex	Zhou et al. [118]	Sequential convex optimization	The proposed method aims to jointly optimize computation offloading and UAV trajectory to minimize energy consumption.
	Zeng et al. [119]	Lyapunov optimization theory, Lagrangian duality theory, and SCA	In that approach, minimize user equipment wait time while controlling energy consumption for a UAV serving a large area.
Optimal offloading	Cao et al. [120]	Iterative Offloading Trajectory and Computation Offloading Algorithm	The proposed approach to multi-sortie UAV trajectory planning and scheduling is to minimize energy consumption.
Mixed discrete and non-convex	Qian et al. [121]	DRL and Lagrangian multiplier method	The goal of the proposed study is to enhance energy efficiency and improve workload computation in UAV-assisted networks.
Optimal association scheme	Han et al. [123]	PSO	The objective of the proposed approach is to minimize the average task delay in UAV-assisted MEC networks.

and a low-complexity offloading strategy for the problem with non-convexness. Li et al. [129] proposed a scheme in which UAVs supply energy to the IoT nodes to support local computing and transmission tasks. By adopting a combination of active and passive transmission to forward the data, IoT nodes can take turns and effectively utilize signals from the UAV. This approach allows the nodes to consume the energy from the UAV for their task transmission and exchange process, and it can increase the communication efficiency in the network. Hu et al. [130] proposed a new model to maximize the total computation bits with UAV for cooperative aerial-ground MECs. The proposed framework is also tailored to the constrained computing power of UAVs while avoiding issues related to non-convexity.

5.2.2. MINLP

To address this issue, Wu et al. [131] investigate the use of UAV-BS to predict and track the location of mobile users, aiming to enhance energy efficiency. The proposed method uses the green-UAV-CoCaCo algorithm to solve the MINLP problem. Tun et al. [132] address the task offloading and resource allocation problem in MEC, with an emphasis on UAVs. The collaboration of UAVs in MEC systems leads to a major enhancement of resource usage, computation latency and energy efficiency. They implement a distributed scalability and cooperation scheme to solve the MINLP problem using the alternating direction method of multipliers. Deng et al. [133] concentrate on maximizing computational efficiency with the aid of multiple UAVs and devices associated with MEC. They proposed a four-stage alternating iterative algorithm designed to maximize computation efficiency, solving the MINLP problem in the system. The proposed approach ultimately promotes deployment optimization and increases task processing speed.

5.2.3. Convex problem

In a convex problem, a UAV provides services such as computational offloading, relay, and communication. The significance of convex optimization in this context lies in the fact that any local minimum, or lowest point in a region, is also the global minimum, or the lowest point overall. This property makes it easier and faster to find the best solution, which is essential for real-time UAV control. Specifically, a problem is considered convex if the line segment between any two feasible points remains entirely within the constraint set, which is usually defined by linear equalities or inequalities [106]. To address this issue, Hua et al. [134] proposed a method involving resource partitioning and bit allocation to minimize the energy consumption of a mobile device, as a countermeasure. They employed dual decomposition, resulting in a convex optimization problem that was effectively addressed. Lee et al. [135] aimed to establish a stable UAV-MEC queue with time-averaged total system energy consumption. Their goal was to reduce the energy required per bit for both mobile UEs and UAV-MECs. To solve this convex problem, they utilized a trajectory control learning model combined with offloading-based proximal policy optimization.

5.2.4. Mixed-integer non-convex programming

To address this issue, El et al. [136] proposed a comprehensive solution for compute offloading in future (tight) IoT applications in pursuit of Ultra Reliable Low-Latency Communication (URLLC). They proposed a mixed-integer SCA-based approach to solving the mixed-integer non-convex programming problem.

5.2.5. Multi-stage stochastic programming

Multi-stage stochastic programming is a method used to solve optimization problems where decisions are made step by step across several stages, such as time slots [137]. In this approach, unknown factors, such as when users send tasks or how the channel behaves, are slowly revealed over time. At each step, decisions can respond to what is known so far, but must be made without knowing everything about the future. To address this issue, Yang et al. [138] enhance the energy and task processing rates of UAVs in a stochastic environment by utilizing the perturbed Lyapunov optimization technique to solve the multi-stage stochastic programming problem. Their proposed approach also yields control decisions in a per-slot manner with the trade-off between system cost and performance, as well as long-term queue stability of data.

5.2.6. Nondeterministic polynomial time (NP)-hard

To address this issue, Nguyen et al. [139] investigate UAV cooperation to improve computation services for mobile users in UAV networks. They implement strategies such as resource pooling, concurrency computing, an improved offloading strategy, and effective task treatment to achieve this goal. Their meta-heuristic solution targets the allocation of communication resources and reduces user delay by recommending a joint plan to UAVs, considering job dependencies.

5.2.7. Multi-objective optimization

Multi-objective optimization aims to optimize multiple objective functions simultaneously. In contrast to single-objective problems, which provide a single optimal solution, multi-objective problems yield a set of compromise solutions. Often, improving one objective worsens another [140]. To address this issue, Peng et al. [141] deal with a multi-objective problem in two steps. They employ the Non-dominated Sorting Genetic Algorithm III (NSGA-III) and design the reliability lazy shadow scheme approach. Additionally, for the delay-constrained scenarios of an aerial computing MEC-based system, they consider the time reliability of task execution and use the backup edge server instances as constraints.

5.2.8. Stackelberg game problem

The Stackelberg game problem is a strategic framework that models and analyzes hierarchical decision-making among independent, rational entities, where the leader moves first and the followers optimally respond [142]. To address this issue, Zhou et al. [143] introduced the flying UAV referred to as a UAV-MEC serve, which combines communication and computation functionalities. Their proposed approach solved the Stackelberg game with a gradient dynamic iterative search algorithm. The UAV is designed to serve in the event of failures at BS caused by different factors.

Table 6 shows different partial task offloading methods based on task type.

5.3. Local processing

It involves executing specific tasks on the device's limited computing hardware, enabling direct computation without transmitting data to an external MEC server [144].

5.3.1. Non-convex

To address this issue, You et al. [145] proposed an iterative algorithm that iteratively updates the resource allocation and the objective value to ensure convergence towards a solution. The proposed methodology aims to reduce the total time required for work completion by judiciously allocating computation, communication, and energy resources. Hu et al. [60] deal with UAV positions, minimizing the energy consumed by the ground users and ensuring successful task computation. They formulated the problem as non-convex and used a penalty dual decomposition-based and 10-norm algorithm. The proposed method results in minimizing energy consumption and ensures successful task computation for all users. Liu et al. [146] proposed a solution based on SCA that combines decomposition and iterative methods. The essential observation is that the energy efficiency of terrestrial users can be enhanced by allowing the idle users to cooperate with active ones on computing tasks. Lyu et al. [147] proposed a method that employs Successive Convex Optimization (SCO) methods to solve nonconvex and nonconcave problems. They developed a BCD algorithm for maximizing the computation bits in the system. Their proposed method addresses the limitations imposed by small computing capability and storage in bounds by utilizing all computation bits in total.

5.3.2. MINLP

To address this issue, Shah et al. [148] address the MINLP problem by using a multistage offloading algorithm that combines learning-based and IPM methods. The author was concerned with abated aftermath of a disaster, and their objective is to position the UAVs to enhance computational efficiency strategically. Jiang et al. [149] proposed an online learning based mechanism called Hybrid learning-based Online Offloading (H2O), aimed at reducing the energy consumption of mobile users. The study first adopted a large-scale path-loss fuzzy c-mean algorithm to locate the ground user and UAV, which then employed four methods. Second, for the problem of mixed integer nonlinear programming, we used a U-based particle swarm optimization algorithm. Third, a sample data set is conducted by a fuzzy membership matrix to train the deep neural network-based scheduling layer. Finally, a hybrid deep learning-based online offloading algorithm for maximizing the overall user equipment energy consumption sum was developed. Zhan et al. [150] proposed an architecture for UAV-assisted IoT devices that have strict deadlines. This problem was formulated as a mixed-integer nonlinear programming problem and solved by the SCA method combined with the KKT algorithm. The aim is to optimize resource allocation, offloading, and path optimization to serve as many IoT devices as possible using UAVs. Dia et al. [151] propose a design that considers the joint role of UAVs and BSs to provide effective MEC services. The problem was modeled as a MINLP problem and solved by a hybrid of heuristic-learning-based scheduling and fuzzy c-means mechanism. This method intends to solve the shortcomings of previous works by jointly considering UAV trajectory, task association, mobile devices' CPU frequency, and wireless transmitting powers. The objective of the considered energy-efficient scheduling problem is to minimize the energy consumption of all mobile users in the UAV-and-BS hybrid-enabled MEC system, subject to satisfying tasks' latency requirements. Seid et al. [152] introduced a multi-agent federated reinforcement learning method to address the MINLP problem. The goal is to minimize latency and energy expenditure under a high-quality level of service.

5.3.3. Optimal stopping time

To address this issue, Callegaro et al. [12] used an optimization problem and an edge-computation algorithm to decide whether a UAV offloads the computation or computes on the device. The UAV needs to identify the optimal stopping time for processing, using a Markov decision process method. This method can effectively reduce both processing latency and power consumption.

5.3.4. Optimal uncertainty

To address this issue, Luo et al. [153] address the problem of uncertainty using an uncertainty minimization-based cooperative target search strategy. Each UAV can determine the optimal strategy for offloading and dynamically chart its path. The proposed method aims to reduce uncertainty across the designated search region.

5.3.5. Integer programming (IP)

IP is a technique that helps achieve objectives by making discrete choices within network constraints [154]. It can be used to reduce energy consumption to extend UAV flight time, minimize service delays for urgent tasks, and increase user capacity to enhance network performance.

To address this issue, Ng et al. [64] proposed a solution that exploits local computation, edge offloading, and Wireless Power Transfer (WPT), which is performed by a two-tier stochastic offloading policy. The proposed method aims to minimize network costs with the stochastic resource optimization methodology, given the uncertainties on wireless charging efficiencies and edge server capabilities.

Table 6
The summary of partial task offloading techniques.

Problem	Reference	Technique	Feature
Non-convex	Zhou et al. [125]	Two-Stage algorithm and three-stage alternative Optimization	The proposed study optimizes the UAV's location, time allocation, computation rate, and task offloading decision.
	Ji et al. [126]	Block alternative descent	The proposed method, which minimizes energy consumption on limited-resource devices, can offload computation to the UAV.
	Bai et al. [127]	Lyapunov-based Online Cooperative	The proposed approach dynamically adjusts task allocation to address the challenges posed by uneven task distribution, thereby effectively reducing delays.
	Xia et al. [128]	Differential evolution and distributed deep neural networks	The proposed study aims to minimize task processing delays and improve overall system performance.
	Li et al. [129]	Two-stage and three-stage alternating iterative algorithm	In that proposed method, the overall network performance improves in the computation of weighted sum bits.
	Hu et al. [130]	Two-layered alternative optimization (TLAO) algorithm	The proposed approach maximizes the total computational capacity in collaborative aerial-ground MEC systems
MINLP	Wu et al. [131]	Green-UAV-CoCaCo algorithm	The proposed study predicts and monitors mobile users' locations to enhance energy efficiency.
	Tun et al. [132]	Alternating direction method of multipliers and Lagrangian relaxation	In that proposed method, improve resource utilization, reduce latency, and optimize energy efficiency.
	Deng et al. [133]	Four-stage alternating iterative computation efficiency maximization algorithm	The proposed solution maximizes computational efficiency in a system that employs multiple UAVs and MEC.
Convex	Hua et al. [134]	Dual Decomposition	In the proposed approach, reduce energy consumption at mobile terminals by implementing resource partitioning and bit allocation on the UAVs.
	Lee et al. [135]	Independent proximal policy optimization	The proposed method aims to decrease the average energy consumption of the overall system for both mobile devices and UAV-MECs.
Non-convex mixed-integer programming	El et al. [136]	SCA-based mixed-integer second-order cone programs algorithm	The proposed approach provides computational offloading to support ultra-reliable and low-latency communications.
Multi-stage stochastic programming	Yang et al. [138]	perturbed Lyapunov optimization-based offloading and trajectory control algorithm	The proposed study focuses on optimizing the energy and task processing rates for UAVs operating in unpredictable environments.
Nondeterministic Polynomial Time (NP)-hard	Nguyen et al. [139]	Metaheuristic	The proposed study aims to reduce user latency and optimize resource allocation for communication.
Multi-objective	Peng et al. [141]	NSGA-III and Reliability-Oriented Lazy Shadow Scheme	The proposed method balances the ideal number of shadow cores with the maximum level of task execution reliability.
Stackelberg game	Zhou et al. [143]	Gradient-based dynamic iterative search algorithm	In that proposed method, UAV-MEC is equipped with communication and computation capabilities to maximize utility service.

5.3.6. Nonlinear programming (NLP)

An NLP is an optimization problem where either the objective function or constraints are nonlinear in the decision variables. These types of problems are fundamental in UAV-MEC systems because communication rates, computation workload, and mobility patterns often follow nonlinear relationships [155]. This complexity makes linear programming less effective, while nonlinear programming addresses the complexity in UAV-MEC optimization models. In contrast, a linear programming problem is an optimization problem in which both the objective function and the constraints are linear in the decision variables [156].

5.3.7. Multi-objective stochastic game

To address this issue, Ning et al. [87] developed a Unmanned Aerial Vehicle Probability-based Strategy Selection Learning (UAVPSSL) and User Equipment Probability-based Strategy Selection Learning (UEPSSL) algorithms for strategy and environment learning. Their proposed method, which employs learning algorithms and optimization inspired by chess, shows how one can achieve efficient computation offloading, as well as optimal placement of edge servers in MEC networks with UAV assistance, even when we consider dynamic settings. Yang et al. [157] introduced a Hierarchical ML Task Distribution (HMTD) model for a target tracking system with a UAV and lower lower-layer pre-trained Convolutional Neural Network (CNN) for vehicle identification, and an MEC server and higher layer CNN for data processing. Seid et al. [158] presented a task offloading and resource allocation scheme with multiple agents, users, and UAVs. Their proposed method used multi-agent DRL represented in a Markov Decision Process (MDP) framework to minimize total computation costs at the network while meeting the quality of service.

5.3.8. Convex Quadratically Constrained Quadratic Program (QCQP)

A QCQP is an optimization problem characterized by a convex quadratic objective and convex quadratic constraints. These problems strike a balance between the simplicity of LPs and the complexity of NLPs, enabling them to be efficient solutions. By optimizing flight paths, resource allocation, and delays for UAVs, QCQPs can boost the performance of UAV-MEC systems, making edge computing faster and more efficient [159].

To address this issue, Mei et al. [91] proposed using UAVs as mobile edge computing servers by integrating onboard computing servers. The proposed method focuses on minimizing energy consumption in both ground terminals and the UAV fixed-wing during hover and aloft flight.

5.3.9. Mixed integer

To address this issue, Qin et al. [160] proposed a framework that leverages DRL and accounts for the age of information. It provides an effective approach to task offloading decisions and computation resource allocation in UAV-edge computing systems, even under uncertain and dynamic working circumstances. Xu et al. [161] solved the mixed integer problem utilizing a task sorting and BCD algorithm that utilizes the priority queue. In this setup, the UAV acts as a relay to

Table 7
The summary of local/full task offloading techniques.

Problem	Reference	Technique	Feature
Integer programming	Ng et al. [64]	Two-stage stochastic offloading	The proposed approach reduces network costs using our stochastic resource optimization method.
Non-convex	You et al. [145]	Iterative optimization algorithm	The proposed method minimizes the overall completion time while optimizing resource allocation.
	Liu et al. [146]	SCA and decomposition and iteration algorithm	The proposed method optimizes the number of bits offloaded by the UAV to minimize total energy consumption.
	Lyu et al. [147]	SCO and block coordinate descent	The proposed approach, which maximizes UAV energy efficiency, enhances ground equipment, leading to a more effective overall system.
MINLP	Shah et al. [148]	Multi-stage offloading algorithm based on a learning algorithm and an interior-point method	The proposed method aims to position the UAVs to improve computational efficiency strategically.
	Jiang et al. [149]	DNN, large-scale path loss fuzzy c-mean algorithm, and U-PSO, H2O	The proposed approach minimizes the energy consumption of the user equipment.
	Zhan et al. [150]	SCA and Karush–Kuhn–Tucker algorithm	In that proposed study, optimizing flight path, resource, and offloading to maximize the number of IoT devices served.
	Dai et al. [151]	Hybrid heuristic and learning-based scheduling and fuzzy c-means algorithm	The proposed method for the energy-efficient scheduling problem aims to reduce device energy consumption.
	Seid et al. [152]	Multi-agent federated reinforcement learning	The proposed method minimizes latency and energy consumption while ensuring high service quality.
Optimal Uncertainty	Luo et al. [153]	Uncertainty minimization-based cooperative target search strategy	The proposed method is an optimal strategy for offloading to minimize uncertainty within the designated search area.
Multi-objective stochastic game	Yang et al. [157]	HMTD	The proposed approach minimizes the weighted-sum cost in UAV communication networks.
	Seid et al. [158]	MDP with multi-agent DRL	The proposed method minimizes the network's overall computational cost while ensuring quality of service.
Mixed integer	Qin et al. [160]	Deep reinforcement learning	The proposed method optimizes the timeliness of information extracted from the computational tasks.
	Xu et al. [161]	Iterative method is based on Block Coordinate Descent	The proposed approach used a joint offloading decision based on task dependencies to reduce energy consumption.
Mixed-integer and non-convex	Sha et al. [162]	DRL	The proposed method minimizes the combined weighted total of task processing delays and energy consumption within the network.
Non-convex and nonlinear	Goudarzi et al. [163]	Two-layer cooperative coevolution	The proposed approach enhances resource allocation for computing while reducing energy consumption.
Optimal stopping time	Callegaro et al. [164]	MDP	The proposed approach optimizes task offloading to reduce latency and energy costs by utilizing local or offloading to UAVs.

delegate some tasks to be processed at the BS. Hence, optimal task assignment and scheduling of the low-priority jobs are required to reduce energy consumption.

5.3.10. Mixed-integer and non-convex

To address this issue, Sha et al. [162] proposed an SDN-based multi-UAV-MEC network, which can obtain the global network information for solving mixed-integer and non-convex. The proposed method's objective is to minimize the weighted sum of task processing delay and energy consumption in the network.

5.3.11. Non-convex and nonlinear

To address this issue, Goudarzi et al. [163] proposed a two-layer cooperative coevolution model that resolves a non-convex and nonlinear problem. The proposed model aims to enhance the allocation of computing resources and save energy.

Table 7 presents a summary of local and full task offloading techniques.

UAV-enabled MEC task offloading methods are taxonomized in Fig. 9, grouped by their primary design focus or methodology. According to this classification, MEC offloading enabled by UAVs is a challenging issue. Focusing on a single category is uncommon when creating an effective method. Instead, it frequently needs to identify the optimal trade-offs (for example, energy vs. latency) utilizing advanced optimization approaches (for example, distributed algorithms or game-theoretic models) to discover a cost-effective solution.

5.4. Cost-based task offloading

In a UAV-enabled MEC system, cost-based task offloading involves strategies to minimize the costs of transferring computational tasks from users or devices, such as IoT sensors or ground users, to UAV-mounted MEC servers or nearby ground MEC servers. Zhao et al. [68] consider the multi-player sequential computation offloading problem and propose the UAV-assisted vehicular computation cost optimization algorithm. Their proposed framework combines SDN technology with the UAV-assisted vehicular computation offloading scheme. Specifically, the UAV offloads computation from the vehicles to the multi-access edge computing server, acting as a relay between the two to reduce the computation cost of vehicles. Deng et al. [71] proposed a method that employs a UAV task distribution algorithm, aiming to minimize the total cost of a UAV-aided target tracking mechanism with the UAV offloading video to an edge node. Huang et al. [165] present a fine-grained offloading approach and design a 3D trajectory optimization method using LOS probability constraint to decrease the optimization area and perform a less time-consuming optimization process. Shen et al. [166] consider the alternative non-convexity problem for the joint offloading strategy optimization. Their proposed approach seeks to reduce the maximum task completion time. Zhang et al. [167] show that Joint Computation offloading, spectrum resource Allocation, computation resource allocation, and UAV Placement (Joint-CAP) is an NP-hard MINLP problem. Their proposed method employs CAP to approximate the algorithm to minimize the IoT device's operation costs in the UAV-assisted mobile edge computing. In their study, Zhang et al. [168] investigated the design of an aerial edge network through

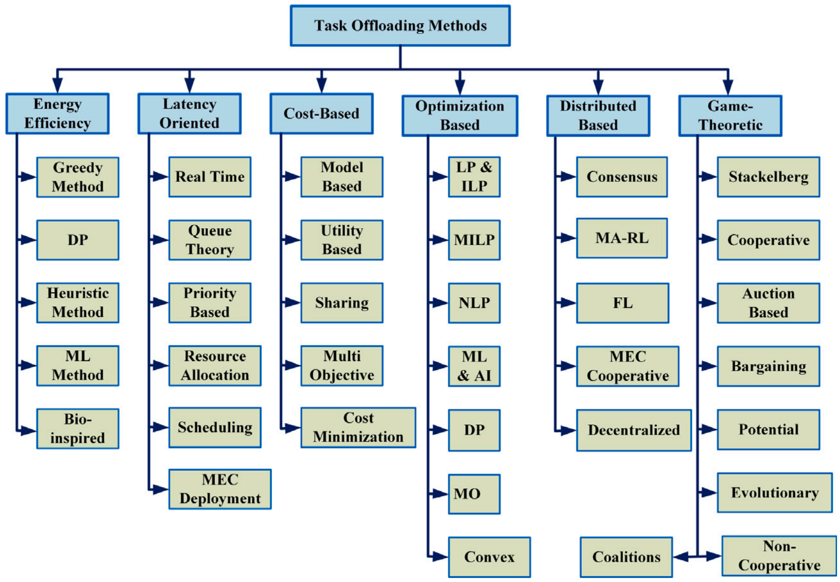

Fig. 9. Taxonomy for UAV task offloading mechanism.

transfer learning to optimize service strategies for UAVs. The proposed system enables the sharing and reuse of prior experiences and environments in protocol optimization. Potential failures in UAVs learning from the beginning are avoided as they access prior experiences. UAVs rapidly alter their edge capabilities due to cooperation among edge units in knowledge sharing. As a result, UAVs engage in rapid decision-making and resource management, thereby enhancing efficiency and resource cost reduction. Hazarika et al. [169] studied the replacement of MEC servers through the design of a DRL-based resource allocation for a roadside unit-deployed system through a DRL-based resource allocation algorithm to solve the limitation.

5.5. Energy efficiency task offloading

For energy efficiency, several methods may be implemented that minimize the energy consumed during the process of transferring computational tasks from ground users to UAV-enabled MEC servers or nearby MEC servers. Such an approach is essential to enhance the sustainability and performance of UAVs and mobile terminals operated in UAV-enabled MEC systems. They may involve the optimization of flight paths, trajectory maintenance, or UAV deployment or positioning in strategic locations, such as mobile computing and energy sources. This optimization method maximizes energy utilization for ground users, extending the network's operational lifespan and improving overall efficiency. Energy consumption is a concern for UAVs, IoT devices, and ground users. To tackle the energy efficiency issues associated with these devices, various methods such as resource partitioning and bit allocation are employed to minimize energy usage on the mobile side [134]. Additionally, the deployment and positioning of UAVs are essential for enhancing energy efficiency for ground users and improving task execution within the network [60].

UAVs can perform dual roles as both power sources and mobile computing platforms, allowing them to offload tasks from IoT devices while supplying the necessary energy for these operations. This dual functionality enhances resource efficiency, optimizes energy use, and facilitates task completion within the network [170]. As discussed in several studies [126,171–175], minimizing energy consumption is a significant challenge in UAV-enabled MEC task offloading mechanisms for both UAVs and mobile users. To address the issue of limited UAV battery life, recharging at microwave stations [176] allows UAVs to operate continuously without the need to land for recharging. With this system, UAVs can hover over user areas to provide computing services while recharging at microwave stations. Furthermore, the techniques used to enhance energy efficiency are a crucial design objective in UAV-enabled MEC systems, given the limited battery life of UAVs and the resource constraints faced by ground devices. Task offloading methods aim to optimize energy usage while ensuring Quality of Service (QoS), low latency, and reliable communication.

The energy efficiency of mobile edge computing networks can be improved by using UAVs as both edge servers and flying energy stations. This setup allows ground users to receive wireless power while offloading computation tasks [177]. Energy consumption in networks with several UAVs handling sensing, communication, and computation can be reduced by altering UAV flight paths, using transmit beamforming, compressing tasks, adopting offloading strategies, and distributing computing resources [178].

A RIS-assisted multi-UAV communication architecture for mobile edge computing networks, seeking to minimize overall system energy consumption while meeting quality-of-service standards for user equipment with unpredictable mobility [179]. A hierarchical optimization method uses a Stackelberg game to make a leader-follower structure for several UAVs. This network uses the K-means clustering algorithm to make it easier for users to associate within the network. The system also uses a model-free DRL method, Soft Actor-Critic, to simultaneously find the optimal power split, set the RIS phase shift, and plan the UAV's path. Non-orthogonal multiple access technology uses the spectrum more efficiently and enables flexible decoding order in dynamic environments with blocks.

Table 8 presents the summary of energy efficiency task offloading methods employed in UAV-enabled MEC systems.

5.6. Latency-oriented task offloading

The UAV-enabled MEC system was proposed to minimize delays in processing and responding to critical tasks requiring real-time data analysis and decision-making. Therefore, a latency-oriented task offloading mechanism in a UAV-enabled MEC system is essential in live video streaming, disaster response, concert programs, collapsed territorial base stations, crowded network environments, and real-time monitoring scenarios. Even slight delays can significantly impact the effectiveness of these operations. Therefore, more efficient decision-making processes enhance edge computing technologies' performance and capabilities to address optimization concepts for real-time applications [194]. Besides, reducing latency is the primary goal to guarantee

Table 8
The summary of task offloading techniques based on energy efficiency.

Reference	Technique	Feature
Li et al. [171]	Double deep Q-network and iterative algorithm	Reduce the overall energy consumption of the MEC system.
Khan et al [172], LV et al. [173], and Yu et al. [174]	Block alternating decent/decomposition/joint optimizing/and FANET and a VisDrone2019 dataset	Minimize Energy consumption of the UAV and user devices.
Hoang et al. [175]	Lyapunov-based online optimization	Minimize the overall energy consumption of both the ground user and the UAV.
Wang et al. [180]	Virtual force field, devise a coordinated flight control algorithm, optimal transport theory, and develop an iterative algorithm	Reducing energy consumption in UAV-enabled MEC networks.
Michailidis et al. [181]	Massive MIMO and weighted total	Reduce energy consumption in these networks.
Gu et al. [182]	Full-duplex protocol	The application of wireless power transfer and multi-access edge computing to transfer computational tasks from UAVs. It also addresses security concerns by utilizing energy harvesting and full-duplex protocols.
Xiong et al. [183] and Qian et al. [184]	Quasi-static scenario and binary offloading scheme /SCA with a Decomposition and Iteration-based algorithm/and IP and successive convex	Minimizing the total energy required by UAV via optimizing the number of bits offloads.
Wang et al. [185]	Multi-agent Q-learning	Minimizing energy use for transmitting during the task offloading and minimizing the total resource consumption in the network.
Liu et al. [186]	UAV-enabled computing communication intelligent offloading	Reduces energy consumption, balances energy usage, and enhances network efficiency.
Wang et al. [187]	Convex optimization-based trajectory and DRL-based trajectory	Minimize energy consumption of all user equipment.
Yang et al. [188]	SCA and Lyapunov-based online control	Minimize the average UAV energy consumption.
Wang et al. [189]	Iterative and ant colony algorithm	Minimize energy consumption in both randomly scattered devices and the UAV-enabled MEC through task offloading and scheduling.
Huang et al. [190]	Heuristic methods	Minimize energy consumption and role division of the UAVs.
Peng et al. [191]	Multi-objective optimization problem	Minimize energy consumption while ensuring the safe flight of the UAV.
Akter et al. [192]	Messy genetic algorithm-based task offloading and power, and computation resource allocation strategy	Minimize the weighted sum of the network's maximum energy consumption ratio and overall task execution latency ratio.
Wang et al. [193]	A greedy heuristic-based dynamic scheduling framework	The primary objective is to reduce both total time delays and energy consumption.

quick data processing [195]. To address the problem of reducing latency, different methods were proposed for strategically transferring computational tasks from ground users to the nearby MEC nodes that are better equipped to handle intensive processing quickly. Therefore, to achieve the strategic transfer of computational tasks, researchers focused on efficiently managing network resources, dynamic selection of MEC nodes, load balancing, proximity, energy efficiency, computational load, etc. Task prioritizing based on bandwidth requirements and urgency, real-time communication protocols, and sophisticated algorithms that can rapidly determine where and when to offload tasks for best reaction times are all necessary for effective latency-oriented offloading. Furthermore, establishing robust, low-latency communication links between UAVs and MEC nodes is crucial, presenting an AI approach to reduce latency and increase throughput in UAV-enabled MEC systems, often requiring the integration of advanced technologies such as 5G/B5G networks, which provide higher speeds and reduced latency [152,196,197]. This emphasis on reducing latency improves the overall dependability and efficiency of UAV-enabled systems in crucial operations and the performance of time-sensitive applications.

Table 9 presents a Summary of the task offloading mechanism based on latency-oriented.

5.7. Distributed task offloading

In UAV-enabled MEC systems, distributed task offloading entails shifting computing workloads from UAVs to neighboring MEC nodes or other UAVs. This strategy seeks to prolong UAV battery life, minimize delay, and maximize resource use. Such methods are essential for UAVs performing data-intensive activities like environmental monitoring and real-time surveillance. The system can process data closer to the collection site by shifting computational activities to edge servers, which reduces the time usually involved in transferring data back to a centralized cloud. A distributed deep learning model [35] was used for computational offloading methods for minimizing delay and energy consumption. With UAV motions being dynamic, MEC resource availability variable, and network circumstances changing, the decision of which tasks to offload, to which node, and at what time is a difficulty [83]. Complex algorithms that can dynamically assess the network's current state, each UAV's energy level, and the computational load are necessary for practical distributed task offloading [202]. These decisions are made using strategies like real-time intelligent positioning algorithms, distributed computation offloading, path planning algorithms, optimization models, and even machine learning algorithms [203]. Distributing the load evenly over the network, ensuring task completion on time, and increasing the operational range of the UAVs, the objectives to improve system performance.

Table 10 presents a Summary of distributed task offloading in a UAV-enabled MEC system.

5.8. Game theory-based task offloading

Game theory can be applied in various scenarios for task offloading, including design, formulation, optimization, and operation in communication and networking [211]. Game theory-based task offloading in UAV-enabled MEC systems models resolves intricate decision-making processes in which numerous interacting agents (UAVs, MEC servers, and end users) search for the best task allocation techniques. Each agent in this situation seeks to optimize utility by balancing computing load, reducing delay, or using less energy. This multi-agent environment can be described as a game where the decisions made by one player

Table 9
The summary of the task offloading mechanism based on latency-oriented.

Reference	Technique	Feature
Hu et al. [195]	Penalty Dual Decomposition based and l0-norm algorithm	Minimize latency and maximize throughput while ensuring user resource allocation fairness.
Wang et al. [196]	Double deep Q-network and deep deterministic policy gradient algorithms	The goal is to enhance system capacity and reduce latency by optimizing UAV placement, resource allocation, and computation offloading.
Huda et al. [197]	DRL-based computation offloading scheme using double deep Q-learning	To make low latency and high computation power.
Ren et al. [198]	DRL with hierarchical trajectory optimization and offloading optimization	Improve real-time scheduling, scalability, and learning efficiency.
Xu et al. [199]	Penalty successive convex approximation method and difference of two convex optimization framework	This study aims to compute the computational maximization of throughput in the network.
Zheng et al. [200]	An iterative algorithm based on block coordinate descent and successive convex approximation techniques	To minimize the maximum completion latency among all devices.
Wu et al. [201]	Ultra-reliable and low-latency communication	It focuses on optimizing computation times, central processing unit frequencies, offloading bandwidths, and the location of UAVs.

Table 10
The summary of distributed task offloading in a UAV-enabled MEC system.

Reference	Technique	Feature
Rahbari et al. [202]	Federated learning, deep reinforcement learning	Improve network fairness and throughput while lowering energy usage and latency via Developing a distributed offloading management strategy with online federated learning deep reinforcement learning.
Chen et al. [203]	Real-time intelligent positioning algorithm, distributed computation offloading, and path planning algorithm	Optimize the efficiency of multiple UAVs by incorporating intelligent positioning algorithms, distributed computation offloading strategies, and energy-efficient design principles.
Luo et al. [204]	The alternating direction method of multipliers	Proposed a two-layer optimized method. Optimize UAV task scheduling and bit allocation, and UAV trajectory.
Duan et al. [205]	Mathematical model and Lyapunov optimization	Concentrate on task scheduling and resource allocation in heterogeneous cloud-aided multi-UAV systems.
Lu et al. [206]	Iterative robust optimization algorithm	The iterative robust optimization algorithm aims to minimize the energy consumption of the UAV-assisted MEC system by optimizing power allocation, CPU frequencies, and the amount of offloaded data.
Li et al. [207]	Deep graph-based reinforcement learning	The UAV scheduling system in the EdgeIoT framework aims to improve overall system performance by reducing the impact of outdated computation tasks on unselected IoT devices.
Huang et al. [208]	Multi-Agent-DRL	A distributed design is proposed for aerial edge networks to enhance energy efficiency in computation offloading and trajectory planning. This design eliminates the requirement for central controllers.
Liu et al. [209]	PSEC algorithm	This approach significantly improves the overall efficiency and performance of computing tasks in distributed environments.
Sun et al. [210]	Markov network-based cooperative evolutionary algorithm	Enhance the effectiveness of data processing and response time for Internet of Vehicle applications.

influence those of the other players through game theory. Cooperative games, in which groups of UAVs or servers cooperate to improve overall results, such as energy savings or faster processing, and non-cooperative games, in which each UAV or server acts independently to optimize its performance, are key game-theoretic strategies. Variables, including the network workload, the energy costs of processing tasks locally rather than offloading them, and the task latency requirements, all influence the decision-making process. To guarantee that each UAV or MEC node's approach leads to a stable equilibrium where no player may profit by unilaterally changing their strategy, game theory offers an organized method for analyzing these decisions.

Asheralieva et al. [212] proposed a hierarchical game theory solution for task offloading that employs a two-level approach. The proposed method involves a hierarchical game theory approach, which models the integration of users and service providers. Additionally, a Q-learning programmatically learn the task offload decision making with the service provider that offers an intelligent QoS to their users. Hu et al. [213] introduced a UAV cluster-based multi-modal multi-task offloading mechanism aimed at allowing collaboration among diverse UAVs to perform various tasks. Yuan et al. [214] proposed a Stackelberg game-based multi-layer framework involving BSs and UAVs as leaders who set the prices and the resource offers, while the mobile users are followers who decide how much to task offload. Their proposed approach ensures that an equilibrium exists/unique, and the solution is directly applicable when a UAV-MEC needs the economic/incentive layer. Chen et al. [215] introduced for task offloading and resource pricing in the UAV-assisted MEC system, which includes flying and the ground MEC server. The proposed method employed a Stackelberg game model to find a pricing game to balance UAV and BS. They demonstrated the convergence of the game-based user allocation and the resource pricing, and the task offloading game-theoretic algorithm to find the decision-making model. Shoaib et al. [216] proposed the decentralized MEC scenario, implementing a stochastic game framework, where each UAV is an autonomous learning agent. The framework allows each UAV to strategize resource allocation. The issue was the dynamic resource allocation, the reward learning algorithm used, and gaming used to find the equilibrium, using learning applicable when designing decentralized and scalable control for fleets of UAVs. Li et al. [217] applied the Nash bargaining to a pure competitive game to solve the cooperative game problem and help with computing offload allocation/resource allocation at the edge. Thus, the Nash bargaining automatically balances the fairness and utility in the outcome, the solution.

Table 11
Comparison of task offloading strategies and approaches in UAV-enabled MEC.

Features	Cost based	Energy efficiency	Latency oriented	Optimization-based	Distributed-based	Game theoretic
Minimize resource cost	Yes	Yes	No	Yes	If considered	If considered
Minimize end-to-end delay	If considered	No	Yes	Yes	Yes	Yes
Decentralized execution	No	No	No	No	Yes	Yes
Central Control mechanism	Yes	Yes	Yes	Yes	No	Some methods used
Dynamic environment	No	No	Yes	No	Yes	Yes
Pricing model	Yes	No	No	Can be integrated	No	Yes
UAV propulsion energy	No	Yes	No	If modeled	If considered	No
Deadline guarantees	No	No	Yes	If considered	Yes	No
Scalability	No	No	No	Yes	Yes	Yes
Real-time processing	No	No	Yes	Yes	No	No
Adoptable for network change	No	No	Yes	Yes	Yes	Yes
Computational complexity	No	No	No	Yes	Yes	Yes
Resource allocation	Yes	Yes	No	Yes	Yes	Yes

5.9. Comparison of task offloading strategies

Distributed-based and game-theoretic task offloading approaches encourage decentralized decision-making despite differences in the processes, goals, and complexity, especially in dynamic, multi-agent UAV environments. Both approaches primarily aim to decentralize job offloading decisions among edge nodes and UAVs, balancing autonomy, scalability, and efficiency without relying on a central controller.

Managing tasks in UAV-enabled MEC requires tailored strategies rather than a one-size-fits-all approach. The chosen strategy depends on the primary objective. If the focus is on cost savings, cost-based strategies are employed to efficiently manage expenses related to computation and data transmission, similar to a budget-conscious planner. For missions where longevity is crucial, energy efficiency strategies take precedence, aiming to minimize power consumption from computing and the essential task of keeping UAVs airborne. In scenarios where speed is critical, such as live video analysis, latency-oriented methods prioritize rapid processing to meet strict deadlines. To implement these strategies effectively, engineers utilize powerful optimization-based tools to determine the best possible outcomes. In more complex, large-scale networks, distributed-based approaches enable individual devices to make intelligent local decisions without relying on a central authority, ensuring system agility. Lastly, game-theoretic methods model the scenario as a strategic interaction, allowing users and service providers to negotiate resources through mechanisms like auctions to achieve a fair and efficient balance for all involved.

Table 11 presents a comparison of task offloading strategies and approaches in UAV-enabled MEC.

6. Optimization techniques

A novel design framework for a system that uses UAVs to help IoT devices with strict deadlines [150]. The objective is to serve as many IoT devices as possible by optimizing the UAV's path, resource allocation, and computation offloading. Design a two-layer training framework that incorporates DRL technology [218]. This framework aims to introduce a decentralized user allocation and dynamic service scheme for assigning UAV deployment in a multi-UAV MEC system. The energy consumption optimization in a UAV swarm-enabled network that supports communication and computation for uncrewed surface vehicles is a critical aspect [115]. Optimizing offloading decisions for USVs can be effectively managed through a UAV swarm-enabled network in the context of time-constrained communication and computation. Furthermore, UAV trajectory optimization and resource management techniques are essential for ensuring effective task execution while reducing energy consumption and communication delays. Optimizing task offloading in UAV-enabled MEC systems is essential for ensuring smooth, reliable, and effective computing and communication services in resource-constrained and dynamic aerial networking environments. Reinforcement learning algorithms that take into account changing user demands and network conditions can be utilized to learn and optimize task offloading strategies over time [219–221]. Multi-UAVs are used for task offloading in a cluster fashion to collaboratively perform different tasks, which proposed a cluster-based multi-modal multi-task offloading mechanism [213]. Table 12 presents a summary of the optimization-based task offloading mechanisms.

Several researchers have used a variety of optimization approaches, including Dynamic Programming (DP), LP, NLP, Integer Linear Programming (ILP), ML, DRL, Multi-Objective (MO), MINLP, and convex optimization, in the context of UAV-enabled MEC systems. These strategies seek to improve communication, energy management, task offloading, trajectory planning, and resource allocation.

Under this section, we present the various optimization techniques that are used to increase the network performance in UAV-enabled MEC.

6.1. Dynamic programming

It is used to solve hard decision problems by breaking them down into smaller subproblems that can be solved again and again, and then putting them back together to find the best solution for the whole problem. It can use overlapping subproblems and optimal substructure, and it works best for sequential decision processes where the solution to one step depends on the solution to the next. For example, multiple tasks are allocated at distinct time intervals t = 0, 1,… T, which are processed either by local or edge servers. The aim is to reduce the weighted delay and energy used to process.

$$x_t = (w_t, E_t, P_t) \tag{1}$$

$$u_t = (b_t, R_t) \tag{2}$$

$$x_{t+1} = f(x_t, u_t, c_t) \tag{3}$$

$$E_{t+1} = E_t - (\alpha_0(b_t) + \alpha_f(w_t, w_{t+1})) \tag{4}$$

Let w_t be the UAV's path, E_t be the energy used, P_t be the tasks that are waiting in the queue, b_t be the binary offloading status, c_t be the channel quality, and R_t be the resources that are available. If the UAV path planning changes because of the trajectory, it needs to be updated. The main aim is to minimize the sum of delay and energy cost in the given T as Eq. (6) and the optimal cost satisfies as Eq. (7).

$$x_{t+1} = f(x_t, u_t, c_t) \tag{5}$$

$$\min_{u_0,\dots,u_{T-1}} \mathbb{E}\left[\sum_{t=0}^{T-1}\Big(w_1 \cdot \text{latency}(x_t,u_t) + w_2 \cdot \text{energy}(x_t,u_t)\Big) + w_3 \cdot C_{\text{end}}(x_T)\right] \tag{6}$$

$$V_t(x_t) = \min_{u_t}\left\{g(x_t,u_t) + \mathbb{E}\left[V_{t+1}(x_{t+1}) \mid x_t, u_t\right]\right\} \tag{7}$$

Table 12
The summary of the optimization-based task offloading mechanism.

Reference	Technique	Feature
Wang et al. [180]	Virtual force field, devise a coordinated flight control algorithm, optimal transport theory, and develop an iterative algorithm	Optimizing communication, computation, and control is becoming increasingly crucial in reducing energy consumption in MEC networks enabled by UAVs.
Seid et al. [219]	Collaboration computation offloading and resource allocation using DRL	This enables effective computation offloading and resource management in dynamic and complex network environments.
Yuan et al. [220]	DRL methods based on prioritized experiences	Optimize task-offloading decisions, specifically in the context of vehicular networks and the advancement of edge computing technologies.
Li et al. [221]	DRL framework based on graph neural networks	The objective is to optimize the offloading of computation tasks to a UAV while considering the computation capacity and battery energy of multiple edge nodes, as well as the UAV's speed limit.
Zhang et al. [222]	The partial computational model used applies the Lagrangian dual method, uses a two-stage iterative algorithm, applies the block-fading channel model	Study to address the problem of computational efficiency maximization in UAV-enabled MEC networks.
He et al. [223]	Multi-objective optimization with MEC selection, resource allocation, and task offloading	The proposed algorithm to solve the problem of joint MEC selection, resource allocation, and task offloading in one way of the road. MEC selection, resource allocation, and task offloading are one way off the road.
Hu et al. [224]	Multi-stage alternative optimization	Enhanced communication efficiency by taking advantage of UAVs' mobility, flexibility, and adaptive capabilities, allowing for optimized resource allocation and an improved user experience compared to traditional fixed-edge servers.
Nguyen et al. [225]	Deep Q-Learning approach	Offering an optimized and efficient solution to the task distribution problem and energy consumption.
Karmakar et al. [226]	DNN-based model, FL, and reinforcement learning based approach	A new approach called Fair Learn was proposed to maximize fairness among secure MEC services in UAV-assisted MEC systems.

6.2. LP, NLP, and ILP

Both the objective and the constraints in LP are linear. NLP has at least one nonlinear constraint, whereas ILP is an LP with the added restriction that its decision variables must be integers. For example, a UAV equipped with MEC resources that allocate bandwidth and computational resources to users aims to minimize total latency. Therefore, the objective function can be formulated as Eq. (8) using LP.

$$\sum_{i=1}^{N}[z_i.(\frac{d_i}{B_i}+\frac{c_i}{y_i})+(1-z_i).\frac{c_i}{f_i}] \tag{8}$$

where each user i has B_i bandwidth, y_i CPU cycles, z_i is the binary decision, D_i is the size of the data to be sent, c_i is the number of CPU cycles needed, and f_i is the local CPU frequency. The main limits are that user i's total bandwidth cannot be more than the total bandwidth, user i's total CPU cycle cannot be more than the total CPU frequency, the minimum quality of service in terms of time taken for transmitted data and computation must be less than or equal to the maximum time transmitted and computed, and a non-negativity limit. In UAVs, MEC is enabled, and NLP techniques are applied to jointly optimize energy consumption. The optimization considers limitations in power, frequency, total computing capacity, and latency. The objective function for this joint optimization can be expressed using Eq. (9).

$$\sum_{i=1}^{N}\left[\alpha\cdot\left(\frac{D_i}{B\cdot\log_2\left(1+\frac{p_i\cdot h_i}{N_0}\right)}+\frac{C_i}{f_i}\right)\right.$$
$$\left.+\ \beta\cdot\left(\frac{p_i\cdot D_i}{B\cdot\log_2\left(1+\frac{p_i\cdot h_i}{N_0}\right)}+\kappa\cdot C_i\cdot f_i^2\right)\right] \tag{9}$$

In UAVs, MEC is enabled, and ILP techniques are applied to the task offloading decision to minimize total cost. The optimization considers task assignment, UAV capacity, time, energy, and link quality. The objective function for task i computed on UAV j can be expressed using Eq. (10).

$$\sum_{i=1}^{N}\left[w_1\cdot t_i+w_2\cdot e_i+w_3\cdot\left(1-\sum_{j=1}^{M}x_{ij}\right)\right] \tag{10}$$

6.3. MINLP

Use MINLP for task offloading in UAV-enabled MEC. The decision involves offloading computing tasks from the ground user to the UAV or to the MEC via the UAV. We can conclude the delay and energy consumption of the computing task k by offloading it. The goal is to minimize the weighted sum of total system energy consumption by jointly optimizing the offloading ratio (α_i), the user-UAV association $\mathbf{X} = x_{i,j}$, and the UAV-MEC relay decision $\mathbf{Y} = y_j$ over the tolerable total delay. The objective function can be formulated as Eq. (11).

$$\begin{aligned}\min_{\alpha,X,Y}\quad & \lambda_T\sum_{i\in\mathcal{M}}T_i^{\text{total}}+\lambda_E\Bigg[\sum_{i\in\mathcal{M}}E_i^{\text{comp}}+\sum_{i\in\mathcal{M}}\sum_{j\in\mathcal{U}}x_{i,j}E_{i,j}^{\text{tra}}\\ &+\sum_{j\in\mathcal{U}}\sum_{i\in\mathcal{M}_j}E_j^{\text{comp}}(i)\\ &+\sum_{j\in\mathcal{U}}y_j\Big(E_{j,\text{mec}}^{\text{tra}}+\sum_{i\in\mathcal{M}_j}E_{\text{mec}}^{\text{comp}}(i)\Big)\Bigg]\end{aligned} \tag{11}$$

6.4. Convex and non-convex

All of the constraints, the objective function, and the feasible set are convex. That means that any local optimum is also a global optimum. But in non-convex optimization, one of them does not meet the condition for convexity. It also has a lot of local optima, which makes it hard to solve. Eq. (12) used convex optimization to find the objective function that would lower the total amount of energy used by computing operations in UAV-enabled MEC. The maximum frequency, latency, and total CPU allocation directly limit the range of solutions that can be found to ensure it works quickly, efficiently, and at a fair price.

$$\kappa\cdot\sum_{i=1}^{N}\quad C_i\cdot f_i^2 \tag{12}$$

Eq. (13) used non-convex optimization to find the objective function that would minimize flight energy while also taking into account a communication constraint that is used by UAV trajectory optimization in UAV-enabled MEC. The minimum data rate, trajectory condition, area, and rate function all put direct limits on the range of solutions.

$$\int_0^T\left[c_1\|v(t)\|^2+c_2\|a(t)\|^2\right]dt \tag{13}$$

6.5. DRL

DRL simplifies the complex UAV-enabled MEC optimization problem by framing it as a decision-making process with the appropriate sequence. It utilizes convex optimization to achieve near-perfect results and can adapt to changing conditions. Assume that a UAV-equipped MEC serves ground users with computationally intensive tasks based on the T time slot, with n duration for each service. The task for the ground user i will be (D_i, C_i, T_i^{max}), which is the data size, required CPU, and the maximum tolerable latency, respectively. In this case, the UAV trajectory, ground users' position, task model, channel model, data rate model, and MDP must be taking in to account. Therefore, the state space as Eq. (14), action space as Eq. (15), and reward function as Eq. (16) will be as follows.

$$s(n) = [s_{uav}(n), s_{user}(n), s_{task}(n), s_{channel}(n)] \tag{14}$$

$$a(n) = [a_{trajectory}(n), a_{offload}(n), a_{resource}(n)] \tag{15}$$

$$R(s, a) = \omega_1 R_{energy} + \omega_2 R_{latency} + \omega_3 R_{fairness} - \omega_4 R_{penalty} \tag{16}$$

6.6. MO

It is an optimization method with two or more goals that are at odds with each other but can be optimized simultaneously. The general mathematical model is Eq. (17).

$$\begin{aligned} &\min_x / max \\ \text{s.t.} \quad &F(x) = \left[f_1(x), f_2(x), \dots, f_K(x)\right] \\ &x \in X \end{aligned} \tag{17}$$

For example, multi-objective joint optimization to reduce energy consumption and latency in UAV-enabled MEC through task offloading and UAV trajectory management. So, the decision variable is Eq. (18). The first goal is to minimize latency (Eq. (19)), and the second goal is to minimize energy use (Eq. (20)).

$$x = (q(t), x_i(t), p_i(t)) \tag{18}$$

$$f_1(x) = \sum_{t=1}^{T} \sum_{i=1}^{N} \left(\frac{D_i}{R_i(q(t), p_i(t))} + \frac{C_i}{f_i(t)} \right) \tag{19}$$

$$f_2(x) = \sum_{t=1}^{T} \left(E_{fly}(q(t)) + \sum_{i=1}^{N} E_i^{com}(p_i(t)) \right) \tag{20}$$

We can employ weighted sums, ϵ constraints, evolutionary algorithms, and multi-objective deep reinforcement learning to address the issue. Table 13 presents a comparison of various optimization techniques.

7. UAV-enabled MEC application

UAVs have a wide range of applications in wireless networks, significantly contributing to improving infrastructure and services. Furthermore, using UAV-enabled MEC, edge computing, such as computational services, is brought closer to users and IoT devices. Within this concept, UAVs operate as flying edge servers, offering ground users or Internet of Things nodes low-latency computing, data caching, and communication services. This is especially helpful in disaster situations, isolated locations, or busy events where terrestrial infrastructure is unavailable, unreliable, or expensive. The main applications of UAV-enabled MEC in wireless networks are as follows:

7.1. Disaster response, search and rescue

Deploying UAV-enabled MEC is often more cost-effective than establishing permanent ground infrastructure, especially in challenging terrains, less populated regions, and during disasters [227]. UAV-enabled MEC can provide real-time video analysis, mapping, and survivor detection in disaster areas and rescue [228].

7.2. Data collection

UAV-enabled MEC equipped with sensors and cameras can collect data over vast areas, enabling real-time data gathering and transmission over wireless networks for monitoring, surveillance, and environmental mapping [229].

7.3. Smart cities

UAVs equipped with MEC servers fly to disaster sites in a smart city, delivering a rapid emergency response. These UAVs provide immediate, localized computing power for processing real-time data from survivors' mobile devices and environmental sensors, even when disasters damage ground-based (terrestrial) communication networks. This allows emergency responders to identify victims faster, assess damage, and coordinate rescue efforts efficiently [230]. This capability facilitates quicker victim identification, damage assessment, and coordination of rescue efforts. This feature enhances the quality of service in smart cities for UAV-assisted applications, such as event management, traffic monitoring, and surveillance.

7.4. Agricultural

Traditional farming involves manual work and postponed decision-making. However, drones and sensors are used in contemporary precision agriculture to increase productivity. Limited connectivity and large data quantities, including pictures and sensor data, make real-time data processing difficult [231]. Therefore, by integrating MEC with UAVs, drones can function as flying edge servers to advance modern agriculture.

7.5. Coverage extension in wireless network

UAV-enabled MEC can be used as flying base stations to temporarily provide network coverage in areas with limited or damaged ground infrastructure and bring computational resources closer to the edge network [232]. This mainly benefits disaster recovery, remote locations, and significant public events.

7.6. Load and information sharing on autonomous vehicles

MEC-capable UAVs can support autonomous vehicle operations by serving as relay stations and mobile computing nodes. Compared to transferring the data to faraway cloud servers, this technique can process the data closer to where it is generated, minimizing latency. Cooperative perception, information sharing and relay, and load sharing are the functions of UAV-enabled MEC [233]. In regions without roadside units/infrastructure [234], UAVs can dynamically deploy MEC services to fill communication dead zones.

7.7. Remote healthcare

Skilled healthcare workers, dependable medical infrastructure, and internet access are sometimes lacking in remote or rural places. Even though patients may have wearable health sensors, quick and dependable solutions are still needed for data processing and medical decision-making. UAVs equipped with MEC capabilities play a significant role in collecting patient health data, processing data in real-time, providing real-time feedback or alerts to medical professionals, and delivering medical supplies [235].

Table 13
Comparison of various optimization techniques.

Technique	Benefits	Drawbacks	Adaptability	Uses
DP	Guarantees optimal solution and sequential decisions	Computationally expensive for large scale and requires complete knowledge	Small or medium size systems	Trajectory planning, energy efficiency, scheduling, and breaking problems into sub-problems
LP	Fast, efficient, and globally optimal solutions	Used only for linear problems and Limited modeling flexibility for complex systems	Simple models and static resource allocation	Resource allocation and task offloading where objectives and constraints are linear
NLP	Models with nonlinear relationships, greater flexibility than LP	Solve non-convex NLPs is hard and gets stuck in local optima	Problems with nonlinear UAV mobility and energy models	Used for nonlinear constraints, Joint optimization, power, and realistic computation
ILP	Handles discrete variables and is useful for binary decision problems	Computationally intensive, NP-hard, and Does not scale well with problem size	UAV selection and offloading decisions in discrete scenarios	Binary task offloading decision, scheduling, and assignment problems
ML	Learns from data without explicit modeling and handles uncertainties in UAV dynamics	Needs large datasets, hard to guarantee optimality, and may over-fit	Predictive resource allocation and demand forecasting in UAV-enabled MEC	Predictive modeling, user mobility, demand prediction, offloading decisions
DRL	Handles dynamic, uncertain environments, learns online policies for large-scale problems, and does not need full system modeling	Training complexity, convergence is not always guaranteed, and simulations or real data are needed	Dynamic resource allocation, real-time UAV path planning, energy-aware offloading	Adaptive decision making in dynamic environments: trajectory optimization, task offloading, and energy control
MO	Provides Pareto optimal solutions and supports multi-metric decision-making	Requires objective normalization and complexity increases with more objectives	Balancing trade-offs in UAV-enabled MEC, e.g., energy with latency	Trade off management between conflicting objectives: energy with latency, throughput with fairness
MINLP	Combine integer and continuous variables and precise modeling for mixed systems	Complex to solve, longer computational time, and scalability issues for large networks	Mixed optimization problems, task assignment, and trajectory planning	Joint continuous-discrete optimization and binary task assignment
convex	Efficient solvers for polynomial time and guarantees global optimal	UAV problems are non-convex by nature	Power allocation and trajectory smoothing under convex relaxations	Energy efficiency, power allocation, and latency minimization

8. Challenges and open issues

UAV-enabled MEC task offloading strategies and optimization mechanisms still face several critical challenges that need to be addressed. This section presents the open issues and research challenges connected to future research directions from the perspectives of offloading strategies and optimization. Basically, the challenges and open issues in this section were divided into three levels based on their relevance to the real-world deployment of UAV-enabled MEC, moving from those most critical or prerequisite to those important for optimization and scale. These are level one, which is reliable and safe; level two, which is operational performance; and level three, which is advanced optimization and enhancement. The goal of level one is to establish a secure and robust communication channel, which is essential for controlling the UAV and sending data. In light of that, the level two takeover requires the UAV to be sufficiently energy-efficient to complete a task and intelligent job allocation techniques to dynamically balance the computational load and provide end customers with the quality of service they desire. Level three is advanced optimization and enhancement that involves integrating mobility and trajectory for dynamic conditions, proactive control using a replica of the digital twin, and intelligent evolution on LLW. To describe the relation between the challenges and open issues, Table 14 presents the details.

8.1. Robust communication

Robust communication in UAV-enabled MEC systems is essential for efficient data transmission, reliability, and security among UAVs, ground stations, and network nodes. Currently, artificial intelligence and machine learning techniques are utilized to process vast amounts of data. UAV-enabled MEC operating within larger IoT ecosystems must tackle challenges related to the heterogeneity and massive scale of IoT devices to ensure effective communication within these intricate networks. Key factors affecting robust communication in UAV-enabled MEC include dynamic environments, mobility, obstacles, interference from other wireless devices, and fluctuating atmospheric conditions. To address these challenges, researchers are investigating various strategies such as interference alignment, dynamic frequency allocation, and spatial multiplexing. Due to the nature of mobility, flexibility, and manageable altitude of UAVs, they can support the wireless system in terms of the fly base station [2,52,58,117,131], enhance wireless network performance as a relay service [3,145], deliver items [236,237], and serve as a computing capability [4]. Currently, UAVs are being integrated into cellular networks to meet the diverse service requirements of the next generation of wireless networks [19,238]. Future communication standards, including B5G and 6G networks, are also a major research focus due to their potential for faster speeds, reduced latency, and improved connectivity [239]. Connecting UAV-enabled MEC communications to these emerging networks is vital [51].

Beyond basic connectivity, a two-layer mechanism improves task scheduling and trajectory in multi-UAV MEC networks [204]. The advanced algorithms, such as delay-aware dynamic offloading [240], further optimize UAV deployment [241] and path planning [242], while ensuring reliability within energy constraints [243].

Furthermore, UAV-enabled MEC systems must accommodate applications with diverse latency, bandwidth, and computing power requirements. To ensure scalability and flexibility, it is crucial to develop standards that facilitate the integration of UAV-enabled MEC systems with existing and future infrastructures and technologies [244,245]. Ensuring service continuity in dynamic scenarios is critical; however, validation in realistic settings is necessary. Therefore, MEC brings computation closer to the user equipment, enabling demanding computations while reducing latency and energy consumption [246].

8.2. Security and privacy

Security and privacy are essential for protecting data integrity, confidentiality, and availability in UAV-enabled MEC systems. One

Table 14
Relation between the challenges and open issues.

Priority level	Challenges	Rational priority
Level 1: Reliability and Safety	1. Robust Communication	Reliable operational prerequisite
	2. Security and Privacy	Safety and trust prerequisites.
Level 2: Operational Performance	3. Energy-Efficiency	Economic operational viability prerequisite
	4. Optimal Task Allocation and Offloading	Main decision-making for MEC performance
	5. Load Balancing and Quality of Service	Performance outcome and depend on levels 1 and 2
Level 3: Advanced optimization and enhancement	6. Mobility and Trajectory	Core UAV advantages and level one solutions
	7. Digital Twin-assisted MEC	Creating virtual replicas
	8. LLM-Enhanced MEC	The next frontier of intelligence and automation

key challenge is improving security procedures to safeguard privacy and data integrity during task offloading [18,247–249]. Researchers are exploring various approaches to tackle this issue, including encryption methods and secure communication protocols [250], the development of intrusion detection systems [251], and the creation of an attribute-based access control model [252]. Additionally, they are focusing on models that address specific security threats and verify data integrity. Techniques such as data anonymization and secure multiparty computation are also being investigated to enhance privacy. Proposed cryptographic protocols aim to protect input privacy while allowing multiple participants to collaboratively compute functions. Currently, frequency-based authentication mechanisms are also pivotal for UAV-enabled MEC systems before establishing a connection. In these systems, various network types, including satellite, B5G/6G, and Wi-Fi, are commonly used. Ensuring data security and integrity across these interoperable networks presents significant challenges, especially when handling sensitive data. It is crucial to design an intelligent task offloading strategy that can withstand jamming attacks [253]. Furthermore, developing techniques that enhance performance by integrating optimizations across multiple network stack layers, including both network and application layers, is essential. Federated Learning (FL) [38] is a good choice for UAV-assisted MEC systems that depend on smart services. These systems let you train models without sharing data. But UAVs are highly mobile, and their topology changes constantly, leading to statistical heterogeneity that causes clients to drop out, stragglers, and models to converge in an unstable way. The distributed FL design and open wireless channels make the system more vulnerable to gradient leakage, eavesdropping, and poisoning attacks. Current FL frameworks also do not work well for aerial networks because they are very mobile and do not like delays. These limitations make it very hard to use UAVs in real life. The lack of realistic UAV-specific datasets and a reliable space-air-ground connection also makes it hard.

Integrating blockchain technology with UAV communication systems can improve security, privacy, and trust in decentralized networks [254]. Using quantum keys and physical unclonable functions, researchers can develop a lightweight and secure UAV-assisted vehicle authentication system that protects communication and defends against both physical and cyberattacks [255]. In addition to enabling secure identification for UAVs operating across multiple regions and diverse vehicle groups, develop an approach that strengthens protocols for vast, dynamic vehicular settings. The security and functionality of UAV-assisted MEC can be further improved by integrating blockchain with cutting-edge technologies like edge computing and artificial intelligence.

Create a lightweight, secure cross-domain authentication system for multi-UAV networks with limited resources by combining blockchain technology with a credit-based trust mechanism [256]. A dual-blockchain architecture that enables decentralized trust management and identity verification across numerous domains by combining private and consortium blockchains. To reduce processing and transmission overhead, they also provide a certificateless signcryption technique. To quickly identify compromised distributed observers and detect anomalous behavior in UAVs, this framework uses real-time behavior monitoring [257]. Additionally, it has a dynamic trust evaluation method that evaluates the legitimacy of UAVs and domains based on feature similarity, cooperation history, and past behavior. Create cross-domain batch authentication protocols that effectively enable large-scale UAV deployments and overcome scalability issues. Vital questions arise: How can we ensure a joining UAV is not malevolent? How can we confirm that an MEC server has not been compromised? And how can we foster confidence among many stakeholders, including end users, MEC service providers, and UAV operators?

8.3. Energy efficiency

The UAV-enabled MEC system aims to create effective, portable energy harvesting solutions that can be seamlessly integrated into IoT devices for ground users or UAVs, without sacrificing weight or mobility. Therefore, optimizing energy usage in UAV-enabled mobile edge computing systems is critical [258,259]. Energy optimization strategies that address the dual challenges of computational task offloading and resource allocation in MEC networks are essential [260]. Enhancing connectivity, energy harvesting, and compute offloading will lead to improved power efficiency for UAVs and IoT devices. A framework based on reinforcement learning should be designed for energy-efficient and resilient task offloading in UAV-assisted MEC systems [261]. Additionally, a strategy for equitable energy distribution among UAVs using convex optimization and joint resource allocation should be developed [262].

To address these challenges, it is necessary to propose several approaches that balance local processing, partial computing, and task offloading to maximize energy efficiency in UAVs and IoT devices while ensuring low latency and sufficient processing power. Given the limited computational capacity, mobility, connectivity, and battery life of these devices, efficient resource utilization is crucial. Furthermore, UAVs can provide both computing services and wireless power transfer to support energy-constrained user equipment [119]. A mechanism should be developed to balance energy savings with equitable service delivery in dynamic, resource-constrained environments, such as disaster relief scenarios [263]. Develop an algorithm that minimizes the average propulsion energy of the UAV over time while stabilizing both the data queue and the perturbed battery queue [138]. Moreover, energy efficiency is essential in UAV wireless communication to extend the duration of communication. Consequently, it is a significant issue that requires heightened attention in UAV communication [264].

8.4. Optimal task allocation and offloading

A crucial aspect of UAV-enabled MEC is enhancing the performance and efficiency of computing resources and task allocation. This involves integrating multiple UAVs with MEC nodes to support applications such as communication services, real-time data processing, and surveillance. Task allocation can become complicated, especially when multiple UAVs and ground users are involved, due to factors like task dependencies, prioritization concerns, and task completion delay constraints [265]. Furthermore, UAVs' rapid mobility affects task distribution and data transmission, requiring consistent network connectivity and design adjustments. In complex UAV-enabled MEC systems, the task allocation and offloading mechanisms must scale effectively to avoid significant performance degradation as the number of UAVs and edge nodes increases. Consequently, developing efficient and intelligent algorithms for optimal task offloading decisions presents a complex challenge. This process must consider various factors, including task characteristics, network conditions, and resource availability [266]. Creating methods for multiple UAVs to collaborate and share tasks can optimize system performance by more efficiently distributing the workload and achieving superior results. It is essential to develop mechanisms to maximize the long-term average system throughput, which refers to the total number of tasks successfully processed in a UAV-assisted MEC system [154]. Additionally, determining whether each mobile device should process data locally or offload it to a UAV is critical [267].

Develop a mechanism to reduce computational delays in a multi-UAV-assisted MEC network [268]. This approach aims to deliver efficient and equitable service in fast-paced, task-oriented environments [269] while effectively managing resources. These factors are essential for enhancing the performance and sustainability of UAV-MEC integrations [270]. Developing methods of task offloading in an MEC system used for reducing delay, minimizing energy consumption, and balancing energy consumption and delay [271] needs researcher attention. Additionally, the task offloading mechanism in UAV-enabled MEC systems provides computing services directly to the user's terminal; in this aspect, computational offloading in MEC systems is the basic research area [272].

8.5. Load balancing and quality of service

The effective allocation of network traffic and compute workloads among multiple UAVs and edge servers is a key focus of load balancing research. The primary objectives are to optimize system performance and enhance user experience. Intelligent load balancing is crucial for applications such as interactive gaming and real-time surveillance systems, as it helps reduce processing delays. However, the mobility of UAVs leads to frequently changing network topologies, complicating load distribution and task allocation. UAV-enabled MEC requires efficient task allocation and offloading related to processing power, storage, and connectivity between terrestrial users and UAVs. Balancing energy efficiency, latency, coverage, and connectivity needs is essential in load balancing [273]. Consequently, these challenges call for further research and the application of deep learning reinforcement mechanisms. To support real-time applications like virtual and augmented reality, as well as video streaming, it is vital to minimize computational and communication delays. Therefore, processing resources in UAV-enabled MEC should be positioned closer to end users to reduce latency and improve application performance. Additionally, optimizing UAV placements and movement patterns is necessary for stable and effective coverage. Finally, maximizing throughput is critical to meet the bandwidth demands of these data-intensive applications. However, achieving QoS requirements while optimizing resource allocation and pricing remains a challenge in UAV-enabled MEC systems [274].

8.6. Mobility and trajectory

In UAV-enabled MEC, mobility plays a vital role in enhancing the communication and computation capabilities of both UAVs and ground users or IoT devices. Therefore, developing techniques that reduce task processing delays in a multi-UAV-enabled MEC network by collaboratively optimizing intelligent flight paths in three-dimensional space is essential [106]. However, the high mobility of UAVs and ground users or IoT devices presents challenges in maintaining service quality for applications that require real-time data processing and low latency. To tackle this issue in UAV-enabled MEC systems, researchers are exploring various approaches. The rapid movement of UAV-MECs leads to frequent changes in pricing and network conditions, which necessitate real-time adjustments for offloading [275,276]. Just as UAVs can dynamically alter their positions, this adaptability enhances demand-aware services. Additionally, it is crucial to develop effective flight route planning algorithms and trajectory optimization techniques [277] that maximize service delivery while minimizing energy consumption. Accurate prediction of UAV trajectories is essential for effectively managing the allocation of computing and networking resources.

8.7. Digital Twin-assisted MEC

UAV-enabled MEC encounters difficulties in highly dynamic, large-scale networks due to computational complexity and the necessity for continuous channel-state information. The new Digital Twin (DT) model for wireless networks is a big step forward for the future. A DT can build a highly accurate virtual model of the physical MEC network, including UAV dynamics, channel states, and user task queues, all of which are updated almost in real time through synchronized sensing [278]. This virtual model enables over-the-air testing or proactive optimization. For example, the joint trajectory and resource allocation algorithm could be run often in the DT to guess network states, test a lot of "what-if" scenarios, and come up with the best control policies (like preemptive UAV redeployment and task scheduling) before sending them to the real system. This is especially important for applications that need to be safe or that need to be fast. Recent research has initiated investigations into DT-assisted task offloading in aerial networks [171] and adaptive DTs for integrated sensing, communication, and computation [279], confirming their ability to address the intricacies of next-generation MEC systems.

In digital twin mobile networks, characterized by limited multimedia training samples, dynamic data variations, and time and privacy constraints, an intelligent framework is proposed that integrates edge computing and few-shot learning [280]. The methods used include using edge computing to process data locally, which lowers transmission latency and improves privacy by encrypting data, and using graph neural networks in the cloud to connect physical systems to virtual representations for semantic inference with very few samples.

8.8. LLM enhanced MEC

It also, as linked networks get better, AI with higher-order thinking skills might be able to organize or improve traditional optimization methods. Because AI can understand and recognize patterns in natural language, large language models (LLMs) are a new way to improve the management of MEC systems. If LLMs could turn high-level operational goals, such as prioritizing disaster response tasks in sectors, into low-level technical constraints or cost functions for algorithms like prioritizing, LLMs on MEC could serve as smart interfaces and decision-support engines. A solid foundation for furthering research and applications is established when edge intelligence and LLMs are combined to create edge general intelligence. The differences between LLM-enhanced EGI and conventional edge intelligence are also made clear. The [281] classifies LLM-driven edge general intelligence systems into centralized, hybrid, and decentralized designs to accomplish this. They examine past use cases, system architectures, and the advantages and disadvantages of each. The performance and effectiveness of a few modest language models on edge devices with limited resources are also assessed in this study. These results make EGI systems more interoperable.

Design a model of generative AI in the next generation of wireless networks [282], and LLMs and mobile edge intelligence are integrated to solve the deployment issues of resource-intensive LLMs on edge devices with constrained resources [283]. The main goal is to ascertain how mobile edge intelligence can facilitate effective LLM deployment by supplying computing capacity at the network edge, such as base stations, to satisfy the stringent latency, bandwidth, and privacy requirements of applications like autonomous driving, virtual assistants, and mobile health.

Specifically, you can train LLM-based agents to analyze both historical and recent network data, such as performance metrics, user requests, and failure logs, to generate code updates for real-time algorithm adjustments and to deliver targeted solutions for troubleshooting and anomaly detection. Integrating LLMs will enable intelligent, user-focused edge computing ecosystems. This will transform network automation from basic optimization to a more adaptive, intent-driven, and transparent process.

9. Conclusion

UAV-enabled MEC has emerged as a promising paradigm to address the limitations of traditional cloud computing, particularly for latency-sensitive and computation-intensive applications. By deploying UAVs as aerial edge servers, computational resources are brought closer to end-users, resulting in reduced latency, lower energy consumption, decreased operational costs, improved service quality, and extended network longevity. This review systematically examined task offloading strategies and optimization methods critical to the performance of UAV-MEC systems. We presented five architectural frameworks tailored to diverse application scenarios, provided a detailed taxonomy of task offloading methods, and analyzed uplink/downlink communication access mechanisms. It addresses critical challenges, including energy efficiency, throughput enhancement, and resource management, offering targeted solutions to meet these objectives. Furthermore, emerging trends, such as the joint optimization of task offloading with trajectory planning and resource allocation, as well as the integration of UAV-MEC with larger systems like non-terrestrial networks. Despite significant advancements, several challenges remain unresolved, including balancing energy consumption with latency, addressing security vulnerabilities, enhancing mobility and channel modeling, effectively coordinating multiple UAVs, creating virtual replicas, and using LLMs in UAV-enabled MEC. The study highlights these open issues as critical directions for future research and unresolved issues, urging researchers to contribute to the ongoing evolution of UAV-enabled MEC.

CRediT authorship contribution statement

Cheru Haile Tesfay: Writing – original draft, Methodology, Conceptualization. **Zheng Xiang:** Validation, Supervision, Conceptualization. **Long Yang:** Validation, Supervision, Conceptualization. **Jabar Mahmood:** Writing – review & editing, Methodology, Conceptualization. **Mengmeng Ren:** Writing – original draft. **Shuangduo Zhang:** Writing – original draft. **Ashok Kumar Das:** Writing – review & editing, Validation, Methodology. **Shehzad Ashraf Chaudhry:** Writing – review & editing, Validation, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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