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Unlocking the Potential of Mobile-Edge Cloud: A Comprehensive Review and Future Directions

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ABSTRACT

With the rapid expansion of the Internet of Things (IoT), the demand for computational resources continues to soar, necessitating innovative solutions to address the needs of resource-constrained IoT users. Mobile edge computing (MEC) emerges as a promising remedy, mitigating the strain imposed by resource-intensive mobile applications. Concurrently, leveraging unmanned aerial vehicles (UAVs) as aerial platforms presents an enticing opportunity to enhance connectivity in wireless networks, owing to their on-demand deployment capabilities, high cruising altitudes, and maneuverability in three-dimensional space. This paper presents a comprehensive examination of UAV-enabled aerial MEC, elucidating its advantages, challenges, and recent advancements across various domains. Topics explored include joint optimization of UAV trajectory, computation offloading, and resource allocation, UAV deployment strategies, task scheduling, load balancing, interplay with other technologies, and machine learning-driven optimizations. Additionally, the paper outlines key avenues for future research endeavors.

Introduction:

In recent years, the explosive growth of the Internet of Things (IoT) has fueled an escalating demand for applications with diverse quality-of-service (QoS) requirements. Many of these applications, such as image/video processing, real-time online gaming, and virtual/augmented reality, demand substantial computational resources and exhibit sensitivity to latency. However, IoT users often encounter limitations in executing these applications due to constrained energy and computation resources. Addressing this challenge presents an unprecedented hurdle for IoT advancement. Enter mobile edge computing (MEC), heralded as a promising solution to this dilemma. MEC servers, strategically positioned at the edge of wireless networks, offer robust computing services to IoT users with minimal transmission and execution latency. By offloading computational tasks to MEC servers, IoT users can significantly diminish task execution latency and energy consumption, thereby expanding support for various computation-intensive and latency-sensitive applications.

However, traditional terrestrial infrastructure-based IoT and MEC networks face limitations in remote or disaster-prone regions where deploying network facilities proves cost-inefficient or unfeasible. Fortunately, a novel paradigm known as UAV-enabled aerial MEC has recently emerged, garnering increasing attention from both industry and academia. Leveraging the inherent attributes of unmanned aerial vehicles (UAVs), including on-demand deployment, low cost, controllable maneuverability, high cruising altitude, and line-of-sight (LoS) connectivity, UAVs serve as aerial MEC platforms suitable for a wide array of applications, spanning civilian to military operations. Aerial MEC functions as a complement to terrestrial MEC networks, particularly when ground base station (GBS)-embedded servers face overload or unavailability. Notably, the LoS connectivity and maneuverability of UAVs substantially reduce task offloading latency and energy consumption for MEC systems. Consequently, aerial MEC, integrating UAV communications and MEC, is poised as a win-win technology for next-generation wireless networks, pivotal in delivering flexible and ubiquitous communication and computing support across diverse environments.

Compared to conventional terrestrial infrastructure-based MEC systems, aerial MEC offers significant advantages derived from UAVs' unique features:

1. Cost-effective and on-demand deployment: UAVs enable rapid, low-cost deployment of aerial MEC systems, catering to real-time demands and offering computation offloading opportunities in areas with sparse or disrupted network facilities.

2. Coverage and computation capacity enhancement: UAVs' higher cruising altitudes allow effective coverage of large areas with fewer UAVs, while forming a flying ad hoc network (FANET) enhances computation capacity in hotspot areas, accommodating more users with high-quality computing services.

3. Reliable LoS offloading links: UAVs' elevated cruising altitudes increase the likelihood of LoS links, providing more reliable wireless connectivity for task offloading and computation result downloading, thus meeting stringent MEC QoS requirements.

4. Energy consumption and latency reduction: UAVs' controllable maneuverability introduces an additional design degree of freedom for aerial MEC. Trajectory optimization coupled with appropriate resource allocation strategies

significantly reduces offloading energy consumption and task latency, outperforming infrastructure-based MEC systems.

Table 1: List of Abbreviations

Abbreviations	**Full Name**
ABS	Aerial Base Station
ADMM	Alternating Direction Method of Multipliers
AI	Artificial Intelligence
ANN	Artificial Neural Network
B&B	Branch and Bound
BCD	Block Coordinate Descent
CTDE	Centralized Training and Decentralized Execution
DC	Difference of Convex
DDPG	Deep Deterministic Policy-Gradient
DNN	Deep Neural Network
DRL	Deep Reinforcement Learning
DVFS	Dynamic Voltage and Frequency Scaling
FANET	Flying *ad hoc* Network
GBS	Ground Base Station
IoT	Internet of Things
IRS	Intelligent Reflecting Surface
LEO	Low Earth Orbit
LoS	Line-of-Sight
MADDPG	Multi-Agent DDPG
MBS	Macro Base Station
MDP	Markov Decision Process
MEC	Mobile Edge Computing
ML	Machine Learning
NLoS	Non-Line-of-Sight
NOMA	Non-Orthogonal Multiple Access
OMA	Orthogonal Multiple Access
PLS	Physical-Layer Security
RL	Reinforcement Learning
SADDPG	Single-Agent DDPG
SCA	Sequential Convex Approximation
SDN	Software Defined Networking
SWaP	Size, Weight, and Power
UAV	Unmanned Aerial Vehicle
WPT	Wireless Power Transfer

Due to the compelling attributes mentioned earlier, significant research endeavors have focused on harnessing the advantages of UAV-enabled aerial MEC. Despite being constrained by stringent size, weight, and power (SWaP) limitations, UAVs exhibit diversified operational altitudes, coverage areas, computation capacities, and endurance levels. Nevertheless, owing to the shared characteristics of different UAV types in communication and computing aspects, aerial MEC can be explored in a unified manner. Performance optimization, considering various constraints, remains crucial across specific application scenarios. Key optimization considerations include trajectory design, resource allocation, optimal UAV deployment, cooperative aerial computing mechanisms, among others. Additionally, research also delves into the interplay between aerial MEC and advanced technologies like wireless power transfer (WPT), physical-layer security (PLS), and reconfigurable intelligent surfaces (RIS) to further enhance performance. Moreover, alongside traditional optimization tools such as convex optimization and game theory, machine learning (ML)-driven optimization has seen widespread application in addressing complex control and resource allocation challenges within dynamic aerial MEC environments. These combined efforts have effectively advanced the application of UAV-enabled aerial MEC across critical domains.

Existing Surveys and Tutorials:

Recent years have witnessed the publication of numerous surveys and tutorials related to UAV communications. For instance, an exhaustive survey categorizing various fifth-generation (5G) and beyond 5G (B5G) techniques based on UAV platforms into domains like physical layer, network layer, and joint communication, computing, and caching has been presented. Similarly, from a game theory perspective, recent progress in modeling and analyzing UAV-aided communication networks has been surveyed, along with the introduction of advanced distributed interference management schemes for large-scale UAV-assisted networks. Furthermore, tutorial overviews of recent advances in UAV-assisted communications and cellular-connected UAVs have been provided, shedding light on UAV integration into networks and their role as new aerial communication platforms and users, respectively. Comprehensive tutorials on the potential benefits and applications of UAVs in wireless communications have also been presented, thoroughly investigating fundamental tradeoffs, analytical frameworks, and mathematical tools for UAV-enabled communication networks. Additionally, recent research efforts on the integration of UAVs with cellular networks, exploiting advanced techniques such as RIS, short packet transmission, joint communication, radar sensing, and edge intelligence, have been outlined to cater to the diverse service requirements of next-generation wireless networks.

Concurrently, representative surveys related to MEC systems have also been conducted. These surveys focused on various aspects such as joint radio-and-computational resource management in MEC systems, MEC orchestration, reference architecture, main deployment scenarios, exploitation of MEC for IoT realization and their synergies, and the definition, advantages, architectures, and potential applications of MEC. Discussions on security and privacy issues and potential solutions, as well as challenges posed by MEC over limited wireless resources, have been addressed. Notably, despite existing surveys and tutorials solely focusing on UAV communications or MEC systems, a comprehensive survey centering on the integration of UAV communications and MEC systems is lacking. Therefore, this paper aims to bridge this gap by presenting an in-depth survey of aerial MEC, envisioning a comprehensive computing infrastructure for future wireless networks.

Paper Contributions and Organization:

As discussed earlier, while UAV-enabled aerial MEC holds promise in providing ubiquitous and reliable MEC services in 5G-and-beyond networks, its successful realization is still in its nascent stage, demanding continuous efforts from both academic and industry communities. Hence, there is a pressing need to review current studies on UAV-enabled aerial MEC. Motivated by this imperative, our aim is to present a comprehensive survey of recent research advances in this domain, categorized by different topics including joint optimization of computation offloading, resource allocation, and trajectory design, UAV deployment, task scheduling, load balancing, interplay with other technologies, and ML-driven optimization for aerial MEC. Moreover, we also offer enlightening guidance for future research directions. The rest of this survey is organized as follows: an overview of aerial MEC is provided in Sec. II, followed by a survey on joint optimization of UAV trajectory, computation offloading, and resource allocation in Sec. III. Then, UAV deployment and load balancing issues are presented in Sec. IV. In Sec. V, the interplay between aerial MEC and other technologies is introduced, followed by a review of state-of-the-art studies dedicated to ML-driven optimization in Sec. VI. Finally, a range of open problems for future research in UAV-enabled aerial MEC is summarized in Sec. VII, followed by conclusions in Sec. VIII. The organization of this survey is illustrated in Fig. 1, and for the ease of reading, a list of abbreviations is provided in Table 1.

Overview of Aerial MEC

Network Architecture

UAVs are categorized based on various factors such as size, weight, wing configuration, flying duration, and altitude, leading to distinctions between large versus small/mini UAVs, fixed-wing versus rotary-wing UAVs, and high altitude platforms (HAPs) versus low altitude platforms (LAPs) [22, 23]. In the context of aerial MEC, different types of UAVs can be deployed to suit diverse application scenarios. For instance, fixed-wing UAVs like small aircraft possess higher flying speeds and longer travel distances, enabling them to carry larger payloads compared to rotary-wing UAVs. However, fixed-wing UAVs must maintain continuous forward motion to stay airborne, making them suitable for covering expansive areas to deliver computing services. Conversely, rotary-wing UAVs like quadrotor drones have the capability to hover stationary over specific locations. Despite their relatively smaller payloads due to size and weight limitations, rotary-wing UAVs offer advantages such as vertical takeoff and landing without the need for runways or launchers, facilitating rapid and flexible deployment. HAPs typically operate at altitudes above 17km and are designed for long-term operations spanning days or even months, catering to applications requiring extensive coverage and endurance.

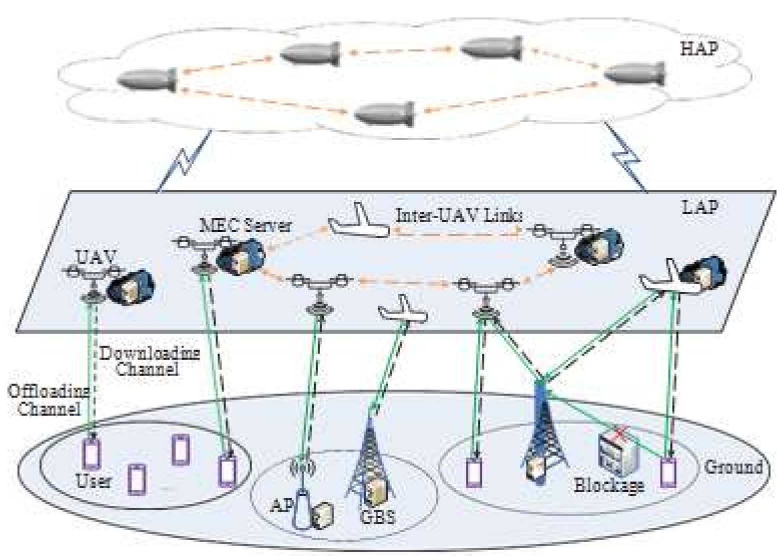


Figure 2: Network architecture for aerial MEC.

An integrated network architecture for aerial MEC is depicted in Figure 2. In regions where network facilities are sparse or even non-existent, UAVs can function as aerial base stations (ABSs) equipped with MEC servers, delivering computing services to mobile users. Additionally, in situations where infrastructure-based MEC within predefined regions may struggle to adapt to fluctuating service demands, UAVs can be swiftly deployed to specified areas to address temporary or unexpected needs. Moreover, UAVs can serve as relays to facilitate task offloading from users to more robust remote MEC servers, potentially spanning two or more hops. Leveraging their ability to adjust positions for optimal channel conditions, UAV relays offer improved performance compared to conventional static relays. However, due to the limited computation capacity of individual UAVs, collaboration among multiple UAVs is essential to expand coverage areas and enhance computation capabilities. Cooperative computing mechanisms necessitate sophisticated design to ensure effective coordination. Furthermore, forming a swarm of UAVs into a Flying Ad-hoc Network (FANET) via inter-UAV links enables efficient task offloading, where smaller UAVs generate task bits forwarded to a head UAV with ample computing resources for real-time processing. Additionally, tasks offloaded from ground users can be redistributed among multiple UAVs within the FANET. Integrating Low Altitude Platforms (LAPs) with High Altitude Platforms (HAPs) and terrestrial infrastructures creates a comprehensive information network. HAPs, with their global perspective, provide broad coverage and computing services, while LAPs supplement terrestrial MEC networks with additional computational resources to ensure stringent Quality of Service (QoS) requirements.

Potential Challenges

The dynamic and intricate nature of UAV communications and MEC systems introduces complexity into the design and optimization of aerial MEC. Despite the evident advantages over terrestrial MEC systems, several pressing technical challenges demand attention:

- Real-time trajectory design: The maneuverability of UAVs introduces a new dimension for aerial MEC design. Crafting real-time trajectories enables better channel conditions for task offloading and result downloading. However, the finite onboard energy of UAVs, coupled with the energy consumption during flight, poses a significant challenge. Moreover, trajectory design must adhere to UAV constraints such as wing configuration, maximum speed, and safe distances between multiple UAVs. Balancing improved channels with energy conservation remains a daunting task, especially considering the interplay with computation offloading and resource allocation strategies.

- Energy-efficient and latency-aware resource allocation: Efficient resource allocation is pivotal for realizing the benefits of aerial MEC. Yet, the multitude of parameters linked to both UAVs and MEC often leads to non-convex optimization problems with high complexity. Addressing the fundamental tradeoff between energy consumption and task latency presents a formidable challenge. Achieving optimal solutions that effectively manage this tradeoff is crucial for aerial MEC deployment.

- Optimal UAV deployment: Enhancing coverage and computation capacity necessitates optimizing UAV deployment, encompassing both 3D placement and the number of UAVs. Altitude optimization is crucial to balance line-of-sight (LoS) connectivity and path loss, considering the increased transmission distance at higher altitudes. Additionally, determining horizontal deployment positions and the minimum number of UAVs for full coverage while meeting service requirements poses a challenging optimization problem.

- Security protection and privacy-preserving: The wireless nature of aerial MEC exposes it to security threats, risking data security and privacy. Small UAVs, with their high availability and ease of deployment, are susceptible to attacks from malicious or rogue UAVs, a threat unique to aerial MEC. Developing robust security mechanisms to safeguard against such threats is imperative.

- Advanced optimization tools: The complexity of aerial MEC optimization often results in high-dimensional problems. Traditional approaches like convex optimization, game theory, and heuristic algorithms require expert knowledge of the environment. In dynamic environments where obtaining expert knowledge is challenging, Machine Learning (ML) tools with adaptive modeling and intelligent learning excel. However, ensuring the optimality of ML approaches remains a challenge, necessitating the identification of diverse scenarios and appropriate selection of optimization tools for aerial MEC.

Joint Optimization of UAV Trajectory, Computation Offloading, and Resource Allocation

Efficient and low-latency MEC relies on adept computation offloading and resource allocation strategies. In the realm of UAV-enabled aerial MEC, the maneuverability of UAVs, despite strict size, weight, and power (SWaP) constraints, presents an additional degree of freedom for enhancing performance. This section delves into the research advancements regarding the joint optimization of UAV trajectory, computation offloading, and resource allocation, categorized by three pivotal UAV roles: aerial base stations (ABSs), mobile users, and relays.

When UAVs Serve as ABSs

Equipped with miniaturized MEC servers, UAVs can function as ABSs, furnishing ground users with prompt communication and edge computing services. The line-of-sight (LoS) links between UAVs and ground users in aerial MEC offer highly reliable air-ground transmissions. However, the amalgamation of UAVs and MEC introduces network heterogeneity and intricate coupling between trajectory design and resource allocation. Consequently, joint optimization of UAV trajectory, computation offloading, and resource allocation strategies becomes imperative.

1) Optimization for the Single-UAV Case: Initial exploration of aerial MEC optimization often involves single-UAV scenarios to glean design insights. For instance, in [27], a lone UAV with an MEC server aids ground users in completing computation tasks, assuming the UAV remains stationary throughout the mission. Energy consumption is minimized by jointly optimizing UAV position, time slot allocation, and computation task partition. Despite the tractable nature of this approach, exploiting UAV mobility remains a challenge, especially in large-scale multi-user scenarios due to closely coupled optimization variables and highly non-convex problem formulations.

Decomposing the original problems into subproblems is a common strategy to mitigate computational complexity [28]. For example, M. Hua et al. [29] decompose the optimization problem into subproblems for resource allocation and UAV trajectory design. Various optimization methods, including ADMM, Lagrange dual method, and linear programming, are employed to tackle these subproblems [30, 31, 32].

Notably, existing literature often focuses on user-centric energy consumption optimization, neglecting UAV energy considerations. Optimizing UAV energy consumption is crucial for prolonging service time, given limited onboard energy and substantial energy consumption for computing and propulsion [33, 34]. Efforts such as [35, 36] address this gap by jointly optimizing task offloading decisions, resource allocation mechanisms, and UAV trajectories, effectively reducing UAV energy consumption. Additionally, the latency problem garners attention, with algorithms proposed to minimize maximum delay among users [37]. A balance between task completion time and UAV energy consumption is crucial, addressed through Pareto-optimal solutions [38].

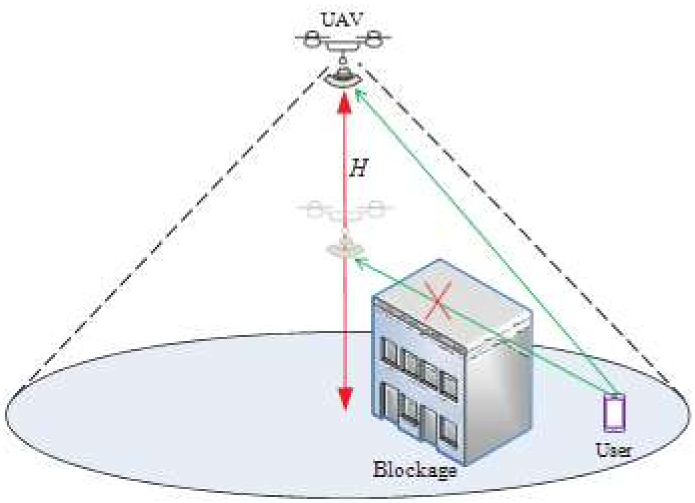


Figure 3 : Illustration of the height optimization for aerial MEC.

In much of the existing literature, UAV flying height is often assumed to be constant. However, in reality, UAVs have the freedom to navigate in 3D space, and their altitude significantly influences air-ground channel gains, affecting the probability of Line-of-Sight (LoS) links and path loss [39]. Therefore, Costanzo et al. [40] delve into the impact of UAV height in aerial MEC and propose a stochastic approximation method for selecting the UAV's flying height.

As depicted in Fig. 3, reducing the altitude can positively affect overall energy consumption due to decreased path loss in LoS conditions. However, below a certain altitude, obstacles may worsen communication links for some users, leading to increased system energy consumption. Hence, there exists a fundamental tradeoff between LoS link probability and path loss when designing the UAV's 3D trajectory. Addressing this, Mei et al. [41] endeavor to jointly optimize resource allocation and UAV trajectory in 3D space to minimize overall UAV energy consumption. They employ the quadratically constrained quadratic program (QCQP) and Block Coordinate Descent (BCD) algorithm to optimize the trajectory of rotary-wing/fixed-wing UAVs in both vertical and horizontal dimensions. Simulation results demonstrate that the UAV's flying height dynamically adjusts to conserve service and propulsion energy while meeting user requirements.

Moreover, the choice of multiple access schemes is pivotal in aerial MEC optimization. While orthogonal schemes like Time Division Multiple Access (TDMA), Frequency Division Multiple Access (FDMA), and Orthogonal

Frequency Division Multiple Access (OFDMA) are common, Non-Orthogonal Multiple Access (NOMA) has emerged to accommodate massive connectivity, reduce transmission latency, and enhance spectrum efficiency [45]. NOMA enables multiple users to access the UAV and offload tasks simultaneously and at the same frequency, mitigating inter-user interference through Successive Interference Cancellation (SIC) techniques. Diao et al. [46] explore NOMA's application in aerial MEC, where users offload task bits to the UAV in the uplink simultaneously via NOMA. They minimize maximum energy consumption among users by jointly optimizing UAV trajectory, task data, and computing resource allocation. Similarly, NOMA-based aerial MEC systems are studied for total energy consumption minimization in [47].

Table 2: Summary of Contributions to the Optimization for Single-UAV Case When UAVs serve as ABSs

Refs.	Optimization Objective	Optimization Variables	Optimization Methods
[27]	User energy consumption	Computation task partition, time slot, UAV position	Augmented Lagrangian active set, 2D search
[28]	Computation efficiency	CPU frequency, power, time slot, UAV trajectory,	Dinkelbach's method, Lagrange duality, SCA
[29]	Energy consumption of users	Bit allocation, connection scheme, CPU frequency, power, UAV trajectory	Lagrangian duality, SCA
[30]	Energy consumption of users	Bit allocation, offloading decision, UAV trajectory	BCD, LP, SCA
[31]	Energy consumption of users	Bit allocation, offloading decision, UAV trajectory	Greedy algorithm, Lagrangian duality, BCD
[32]	Energy consumption of users	Bit allocation, UAV trajectory	ADMM
[35]	Energy consumption of both users and the UAV	Bandwidth, bit allocation, CPU frequency, power, UAV trajectory	BSUM
[36]	Energy consumption of both users and the UAV	Bit allocation, CPU frequency, UAV trajectory	Lyapunov optimization, ADMM
[37]	Sum of the maximum delay among all users	Offloading decision, offloading ratio, UAV trajectory	PDD, CCCP
[38]	Energy consumption and completion time of the UAV	CPU frequency, offloading decision, UAV trajectory	SCA, Pareto-optimal
[40]	Long term system average energy consumption	CPU frequency, transmission rate, UAV height	Stochastic optimization, Kiefer-Wolfowitz algorithm
[41]	UAV energy consumption	Bandwidth, power, CPU frequency, UAV's 3D trajectory	Lagrange duality, SCA, QCQP
[46]	Maximum energy consumption among all users	Bit allocation, CPU frequency, UAV trajectory	SCA
[47]	Energy consumption for offloading and computing	Bit allocation, power, UAV trajectory	SCA, Lagrange duality
[48]	Energy consumption of users	Bit allocation, UAV trajectory	SCA
[49]	Weighted sum energy consumption of users and UAV	Bit allocation, CPU frequency, UAV trajectory	BCD, SCA, Lagrange duality
[50]	Energy efficiency	CPU frequency, power, UAV trajectory	Dinkelbach's method, SCA, ADMM

Simulation results demonstrate the superior energy efficiency of NOMA compared to orthogonal multiple access (OMA). Jeong et al. [48] minimize total user energy consumption under both NOMA and OMA schemes, considering task tolerance latency and UAV energy budget constraints, using the Successive Convex Approximation (SCA) technique. Similarly, in [49], the joint optimization of UAV trajectory and computation resource allocation minimizes the weighted sum energy consumption of UAVs and users, exploring both OMA and NOMA schemes with the Block Coordinate Descent (BCD) method. Li et al. [50] focus on enhancing user experience while maximizing UAV energy efficiency for OMA and NOMA schemes, jointly optimizing UAV trajectory, user transmit power, and computation load allocation using the Dinkelbach algorithm and SCA technique to solve the non-convex fractional programming.

A summary of contributions to joint optimization for the single-UAV case when UAVs serve as ABSs is provided in Table 2.

For the multi-UAV case in aerial MEC, relying on a single UAV for edge computing presents limitations due to onboard energy storage and computing capacity constraints, as well as limited coverage area. To address these, multiple UAVs are deployed as ABSs with MEC servers, offering more robust and extensive edge computing services [52]. However, leveraging multiple UAVs introduces challenges. Users must decide both task offloading amounts and which UAV to offload to, known as the user association problem. Additionally, joint optimization of user association, UAV trajectories, and resource allocation becomes more complex than single-UAV aerial MEC systems due to increased variables and closer coupling. Furthermore, ensuring safe distances among multiple UAVs to avoid collisions complicates trajectory design.

Recently, efforts have been made to address the challenges faced by multi-UAV aerial MEC systems. Various solutions have been proposed, targeting user association among other issues. Zhang et al. [54] aim to maximize computation efficiency in a multi-UAV-enabled aerial MEC system. They jointly optimize user association, CPU frequency allocation, power and spectrum resources, and trajectory scheduling of multiple UAVs using an iterative algorithm with a double-loop structure. User association is formulated as a standard integer linear programming (ILP) problem, which can be solved using algorithms like branch-and-bound (B&B) and cutting plane methods. Diao et al. [55], on the other hand, propose a greedy-based offloading strategy variable rounding (GOSVR) algorithm to achieve a near-optimal solution for user association. They then optimize UAV trajectories to minimize the weighted sum of maximum energy consumption among users and UAVs. In [56], the sum power minimization problem is decomposed into subproblems, and the user association subproblem is approximated as a sequence of weighted l0-norm minimizations. A compressive sensing-based algorithm is proposed to obtain the closed-form solution. However, note that the location planning of UAVs in [56] is obtained through one-dimensional searching without considering UAV mobility.

In another approach, trajectory design and resource allocation for NOMA-based multi-UAV aerial MEC are jointly optimized in [57]. The problem is decomposed into two subproblems, and an efficient iterative algorithm is proposed to minimize the weighted sum energy consumption of users and UAVs. Each iteration solves the resource allocation subproblem using Successive Convex Approximation (SCA) given UAV trajectories, and the trajectory planning subproblem for multiple UAVs is addressed via quadratic approximation based on resource allocation schemes. Building on this, Qin et al. [58] focus on the multi-access feature in multi-UAV aerial MEC systems and propose a joint trajectory design and resource allocation algorithm. With multiple radio access, each user can offload task bits to multiple UAVs simultaneously for parallel computing. The proposed algorithm outperforms fixed trajectory, fixed bandwidth allocation, and single access schemes.

It's important to note that the literature discussed assumes users in multi-UAV aerial MEC systems act rationally, making offloading decisions in a risk-neutral manner to maximize their perceived utility, like minimizing energy consumption [56] or maximizing computation efficiency [54]. However, in reality, users tend to exhibit risk-seeking or loss-averse behavior due to uncertainties in computing resource availability [59, 60, 61]. Specifically, as the energy available for computing decreases over time due to UAV energy consumption during flight, uncertainty arises regarding the UAV's ability to process offloaded task bits. Taking both risk-aware user behavior and UAV computing resource availability into account, Apostolopoulos et al. [53] aim to maximize user satisfaction utility, introducing a linear probability of failure function to describe UAV computing resource availability. Simulation results demonstrate superior performance compared to alternative approaches. Moreover, users' physical and risk-aware characteristics significantly influence their task offloading decisions. UAVs with higher computation capability and more energy storage receive more task bits from users.

Despite extensive optimization efforts for multi-UAV aerial MEC, most assume each UAV operates independently, computing users' tasks based on their own capacity, which may lead to overload if UAVs take on too many tasks. Balancing UAV load by adjusting user association is a potential solution. However, users within the coverage of an overloaded UAV may be too far from other UAVs, making user association adjustment impractical. Alternatively, multiple UAVs can cooperate in the air to share their capacities, reallocating task data among them using inter-UAV links [62]. Illustrated in Fig. 4, via inter-UAV links using various radio interfaces like WiFi, millimeter wave (mmWave), and 5G New Radio (NR), a swarm of UAVs can form a FANET, exchanging information including task data, control, and coordination information [63]. Although task reallocation imposes additional transmission delay and overheads, computation capacity sharing holds potential to reduce task processing delay and energy consumption for multi-UAV aerial MEC systems.

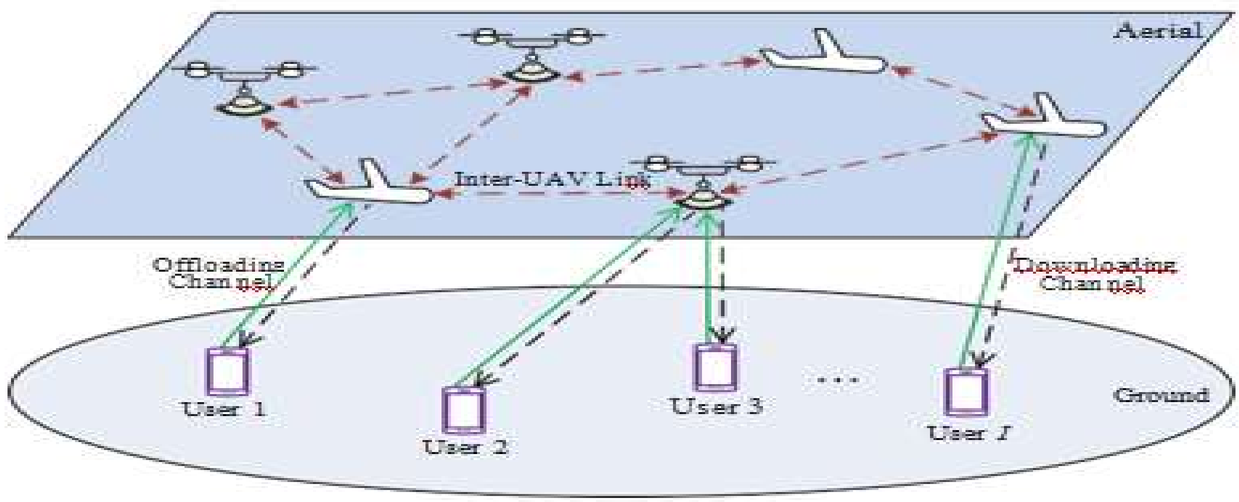


Figure 4: Cooperative aerial MEC via the inter-UAV links.

Currently, research on cooperative MEC among multiple UAVs is still in its early stages. In [64], a collaborative MEC model involving multiple UAVs with inter-UAV links is explored. When a UAV in a defined area receives a sequence-dependent computing task, it can distribute sub-tasks to other UAVs via inter-UAV links. A spatial branch limiting algorithm is introduced to minimize the overall energy consumption of the UAV cluster. Results indicate that when the number of tasks is small, a single-UAV scheme consumes less energy than the proposed multi-UAV collaborative MEC. However, as the number of tasks increases, the single-UAV scheme may not complete all tasks, while the collaborative MEC with multiple UAVs can, as computation capacities are shared through inter-UAV links. In [65], tasks from UAV users are offloaded to other UAVs via FDMA-based inter-UAV links. A strategic game is used to analyze UAV interactions, and a decentralized strategic offloading algorithm is proposed to optimize UAV energy consumption. Similarly, in [66], UAVs with low-latency and computation-intensive tasks can offload partial task data to nearby UAV helpers with more powerful computing abilities. A two-stage resource allocation scheme aims to minimize total energy consumption using convex optimization and stochastic learning automata. Additionally, K. Yao et al. [67] investigate cooperation between two types of UAVs, scout UAVs (SU) and computing UAVs (CU), within a UAV swarm. A game-theoretic approach addresses computation offloading and variable-width channel access, minimizing overall UAV energy consumption.

In addition to energy consumption optimization, R. Chen et al. [68] focus on delay minimization in cooperative UAV swarm-assisted MEC systems. UAVs in a swarm are grouped into coalitions consisting of a leader and multiple members. Each member UAV must decide the offloading ratio and transmission channels to the leader UAV to minimize computing delay. An exact potential game is formulated to achieve Nash equilibrium.

Considering trajectory design in multi-UAV aerial MEC systems, collision avoidance is crucial in real environments. UAVs need to maintain a safe distance from no-fly zones or obstacles [54] and from each other to prevent collisions [55]. In [51], multiple UAVs are assumed to fly at different fixed altitudes to avoid interference. Advancing further, a conflict elimination strategy in [69] ensures minimum distances among potential conflict UAVs adhere to safety constraints. Additionally, [70] proposes a reinforcement learning approach for UAV path design, incorporating collision risk into the reward function to prevent collisions.

A summary of contributions to the joint optimization for multi-UAV cases, where UAVs act as ABSs, is presented in Table 3.

When UAVs Serve as Mobile Users

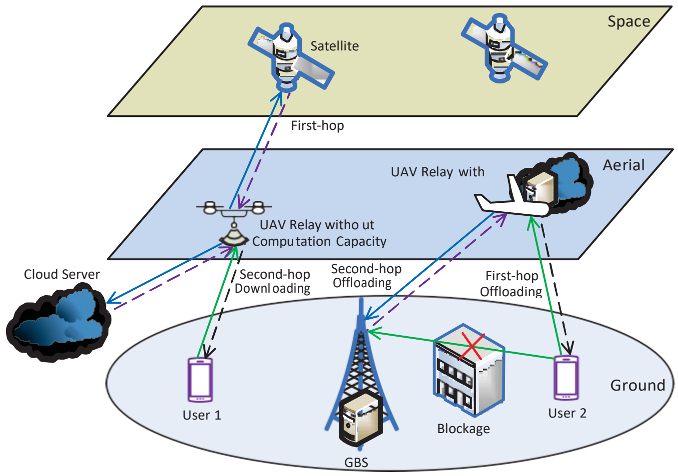
UAVs offer advantages such as low cost, on-demand deployment, and high maneuverability, enabling them to serve as mobile users for critical tasks in various scenarios, including target tracking, emergency rescue, smart delivery, and mapping. However, due to energy and computation capacity limitations, UAVs may struggle to process collected data in real time. To overcome this challenge, computation tasks can be offloaded to powerful MEC servers deployed at GBSs or other BS entities. Unlike ground users, UAVs can adjust their positions in 3D space to optimize channel conditions for task data offloading.

In scenarios where UAVs serve as mobile users, [78] employs fixed-wing UAVs to transmit collected data to ground MEC servers for real-time processing. Optimizing the weighted sum energy consumption of the UAV and MEC server involves joint optimization of UAV trajectory, task assignment, and CPU computational speed, considering constraints such as UAV and server computation capacities, UAV velocity, and acceleration. Interestingly, the transmit power of fixed-wing UAVs significantly influences trajectory and energy consumption. A smaller transmit power results in trajectories resembling an "8," requiring continuous acceleration and deceleration to hover closer to ground MEC servers, thus consuming more energy. Conversely, higher transmit power enables task completion even with worse channels, resulting in trajectories with lower average acceleration and energy consumption savings. Similarly, [25] explores aerial MEC systems where multiple UAVs act as users associated with an MEC server for computation offloading. Considering access schemes like TDMA, OFDMA, one-by-one access, and NOMA, total UAV energy consumption is minimized using SCA. NOMA demonstrates superior energy consumption performance over OMA, yet superposition of all UAVs on the same resource block can cause severe decoding delay and co-channel interference. Addressing this, a multi-UAV grouping method in [79] reduces the number of UAVs on the same resource block. Subsequently, optimization of UAV transmit power and BS computation resources, based on KKT conditions, minimizes the sum of energy consumption related to communication and computing.

Although lower energy consumption benefits UAVs with limited battery storage, QoS, particularly transmission and execution delays, is crucial for UAVs performing critical tasks as users. [81] proposes an energy-efficient offloading scheme for UAVs based on transmission and execution delay. A matching scheme selects optimal partners between UAVs and edge nodes, and offloading is modeled as a bargaining game to maximize utility.

Table 3: Summary of Contributions to the Optimization for Multi-UAV Case When UAVs serve as ABSs

Refs.	Optimization Objective	Optimization Variables	Optimization Methods
[54]	Computation efficiency	Bandwidth, CPU frequency, power, UAVs' trajectories, user association	Dinkelbach's method, SCA, ILP
[55]	Sum of the maximum energy consumption among users and UAVs	UAVs' trajectories, user association	Greedy algorithm, SCA
[56]	Weighted sum power of users and UAVs	Computation capacity, power, UAVs' locations, user association,	Compressive sensing, Lagrangian duality
[57]	Weighted sum energy consumption of users and UAVs	CPU frequency, power, UAVs' trajectories	Quadratic approximation, SCA
[58]	Weighted sum energy consumption of users and UAVs	Bandwidth, bit allocation, CPU frequency, power, UAVs' trajectories	BCD, SCA
[64]	Energy consumption of UAVs	Bandwidth, bit allocation	B&B
[65]	Energy consumption of UAVs	Bit allocation	EPG
[66]	Energy consumption of UAVs	Channel, offloading decision and rate	SLA
[67]	Energy consumption of UAVs	Channel, offloading ratio	EPG
[68]	Total delay of UAVs	Channel, offloading ratio	EPG
[69]	Energy consumption of users	Bit allocation, UAVs' trajectories, user association	Dynamic programming, ADMM



A balance is achieved by employing Lyapunov optimization, leading to the discovery of the optimal task scheduling and resource allocation strategy.

In addition to MEC servers in close proximity to UAVs, satellites or other BSs equipped with MEC servers can offer additional offloading opportunities for UAVs. For example, in [84], a fleet of small UAVs on an exploration mission can offload tasks to a nearby WiFi BS or a more powerful cellular-connected MEC server. A non-cooperative game theory-based algorithm addresses UAVs' offloading decisions, resulting in significant energy savings for computation offloading with the appropriate communication medium. Similarly, [85] utilizes UAVs to detect wind turbines, after which both ground MEC servers and satellites can provide edge computing services for the UAVs. To minimize completion time, UAV trajectories and computation strategies are jointly optimized. It is demonstrated that the proposed ground-satellite-integrated offloading scheme achieves lower completion time than the scheme without satellites, highlighting the advantages of introducing satellites for offloading opportunities.

A summary of contributions to joint optimization when UAVs serve as mobile users is provided in Table 4.

When UAVs Serve as Relays

For users with limited local resources located in remote areas or with direct links to BSs blocked by obstacles, UAVs can serve as relays to forward computation-intensive tasks to more powerful remote MEC servers via two or more hops. An illustrative network architecture when UAVs serve as relays is depicted in Fig. 5. Compared to conventional static relays, UAV relays offer opportunities for system performance enhancement as UAVs can adjust their positions for better channel conditions. However, the participation of UAV relays makes UAV trajectory design more complex, and optimization of computation offloading and resource allocation is essential to fully utilize the potential of UAV relays in aerial MEC.

1) UAV Relay without Computation Capacity: In [87], as ground channels from IoT nodes to the data center suffer severe fading, UAVs serve as relays to forward information from IoT nodes to the data center controlled by the fog

computing BS. To maximize IoT nodes' throughput, subcarrier allocation, transmit power of IoT nodes and UAV, as well as UAV trajectory are jointly optimized. Simulation results show that throughput of IoT nodes under mobile UAV relay is higher than that under static UAV relay. In [88], with UAVs acting as mobile relays between users and the BS, UAV trajectory, power allocation, and user scheduling scheme are jointly optimized to minimize the total latency of all users.

UAV Deployment, Task Scheduling, and Load Balancing

With UAVs increasingly used in civilian and military settings, effective UAV deployment for maximizing coverage and capacity has become a challenging aspect of aerial MEC [99]. While significant work has been devoted to UAV trajectory planning to offer high-quality edge computing services, existing approaches often assume UAV deployment within predefined regions with fixed user locations. However, in practice, user distribution varies over time. For instance, as shown in Fig. 1 of [100], service requests in places like Happy Valley theme park in Beijing exhibit highly nonuniform distributions, forming hot-spot areas at different locations and times throughout the day. Consequently, deploying UAVs within predefined regions may not adequately address the dynamic distribution of users and service demands. Moreover, to conserve energy and simplify network management, the number of deployed UAVs should be minimized while ensuring all tasks meet latency requirements [101]. However, determining the minimum number of UAVs needed for full coverage while meeting task requirements cannot be solely achieved through trajectory planning. To tackle these challenges, deployment parameters of UAVs, including horizontal position, flying height, and the number of UAVs, need to be jointly optimized.

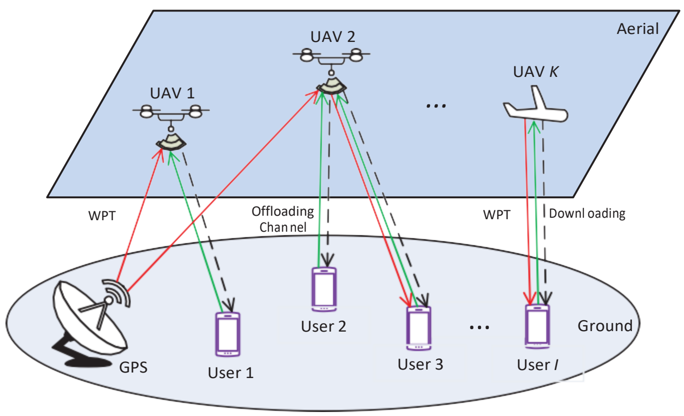
UAV Deployment in 2D Space

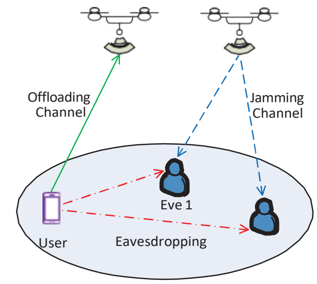
Multi-UAV deployment optimization is generally regarded as an NP-hard problem [102]. Differential Evolution (DE) is considered an effective method to address this problem and find satisfactory solutions [103]. DE mimics biological evolution, retaining populations that adapt to environments through iterations. In [103], a DE-based multi-UAV deployment mechanism is proposed to obtain near-optimal 2D UAV positions iteratively. This algorithm ensures load balancing of UAVs while satisfying coverage constraints and IoT nodes' Quality of Service (QoS) requirements. Additionally, a Deep Reinforcement Learning (DRL) algorithm is devised for task scheduling to enhance task execution efficiency. Similarly, DE-based algorithms are proposed in [101, 104] to optimize UAV deployment with objectives such as minimizing system energy consumption [101] and load variance of UAVs [104]. The effectiveness of DE-based algorithms in reducing energy consumption and the number of deployed UAVs is demonstrated in [101].

To address unexpected or temporary high traffic loads in hot-spot areas, H. El-Sayed et al. [105] explore UAV deployment in vehicular networks, where UAVs are dynamically deployed as mobile edges. Using Bee Swarm Intelligence (BSI), a UAV deployment approach is proposed to achieve full network coverage without additional overhead or delay. Similarly, on-demand UAV deployment for hot-spot areas is studied in [100], aiming to maximize the number of served tasks. A variable-sized bin-packing problem with geographic constraints is formulated to optimize hover locations of UAV-mounted edge servers among dynamic hot-spot areas. Since the bin-packing problem is NP-hard, an online dispatching scheme is proposed to find UAV hover locations, and a greedy algorithm is developed to assign tasks to UAV-mounted edge servers. Real-world experiments demonstrate that this UAV dispatching scheme can timely serve more users in hot-spot areas while achieving high resource utilization.

In contrast, X. Wang et al. [106] focus on the economic viability of UAV-provided services (UPS) in hot-spot areas. They find that if a UAV encounters multiple hot spots, it should deploy to serve a single hotspot, considering optimal pricing and energy allocation for each hotspot. For cases involving multiple UAVs, a counterintuitive observation is made: with UAVs deploying to different hot spots, more UAVs may be deployed to the second-best hotspot instead of the expected first-best one for profit-maximizing purposes.

2D/3D Space	Refs.	Optimization Objective	Optimization Variables	Optimization Methods
2D	[100]	Number of served tasks	UAV positions and task assignment	Online dispatching and greedyalgorithm
	[101]	System energy consumption	Number and positions of UAVs, task scheduling	DE, greedy algorithm
	[103]	Load balancing and execution la-tency	UAV positions, task scheduling	DE and DRL
	[104]	Load balancing	Number and positions of UAVs, task offloading decision	DE
	[105]	QoS in vehicular networks	UAV positions	Swarm intelligence
	[106]	Total profit of UAVs	UAV positions, service price, hovering time and servicecapacity	Backward induction
	[113]	Long-term profit of UAVs	UAV positions, communication and computation re-sources	Lyapunov optimization
	[114]	Throughput of task offloading	Coalition selection of ground nodes, UAV positions	Coalition formation game,Stackelberg game
	[115]	Coverage efficiency	Cluster head selection, UAV positions and transmit power	Penalty and BCD
3D	[107]	Operating latency of UAVs	UAV positions and user association	SCA
	[108]	Average time delay of users	Number and positions of UAVs, task offloading decision	SGD
	[109]	Number of deployed UAVs	Number and positions of UAVs, user association, task of-floading decision	Meta-heuristic algorithm
	[112]	Coverage efficiency	Number and positions of UAVs	PSO





Interplay between Aerial MEC and Other Technologies

WPT-Integrated Aerial MEC

Wireless Power Transfer (WPT) has emerged as a promising technology for providing stable and controllable energy supplies to users equipped with Energy Harvesting (EH) modules, extending their operational lifetimes [116, 117]. In the context of aerial Mobile Edge Computing (MEC), as depicted in Fig. 6, WPT-integrated systems have garnered increasing attention from both industry and academia. For instance, in [118], a single UAV integrates a Radio-Frequency (RF) energy transmitter and an MEC server to offer wireless energy supplies and computing services to ground users. An alternative algorithm, based on Successive Convex Approximation (SCA) and Lagrange duality, is employed to minimize the UAV's energy consumption. Subsequently, in [119], the maximization of computation rate in WPT-integrated aerial MEC is explored under energy-harvesting and UAV speed constraints. Simulation results show that increased UAV transmit power leads to a rise in the weighted sum of computation bits for all users, enabling better energy harvesting and task offloading. Additionally, [120] introduces a new TDMA-based workflow model for wirelessly-powered aerial MEC systems, optimizing user association, computing resource allocation, UAV hovering time, wireless powering duration, and service sequence to minimize UAV energy consumption.

Given the broadcast nature of wireless links, UAV transmit power can charge not only active users but also idle ones to prevent power wastage. To address this, Y. Liu et al. [121] propose that idle users harvest energy from the UAV and assist active users in computing tasks. By optimizing resource allocation and UAV trajectory, energy consumption is reduced while maintaining active users' task completion within tolerable latency. Moreover, the near-far effect, wherein users farther from the UAV harvest less energy despite needing to communicate over longer distances, is mitigated by leveraging closer users as relays [122, 123]. This reduces the communication distance for farther users, saving transmission energy harvested from the UAV.

In scenarios where UAVs themselves face battery limitations, EH modules can be deployed on UAVs to harvest energy from Ground Power Stations (GPS) or other sources [124, 125]. Y. Liu et al. [124] address service utility maximization by jointly optimizing UAV trajectory, computation offloading decisions, and offloading duration. They find that service utility initially increases sharply with GPS transmit power, enabling the UAV to adjust its trajectory to undertake more offloading tasks. However, once suboptimal offloading duration and UAV trajectory are achieved, further increases in harvested energy have minimal impact on service utility.

Interestingly, UAVs can serve not only as information relays and MEC servers but also as energy relays to broadcast energy harvested from Access Points (AP) to User Equipments (UE). Y. Xu et al. [98] maximize the weighted sum of completed task-input bits of UEs by optimizing task allocation, UAV Wireless Power Transfer (WPT) power, offloading and execution time, and UAV trajectory using a three-step Block Coordinate Descent (BCD) algorithm. They find that UAV trajectory strongly depends on AP location, incentivizing the UAV to move closer to the AP to harvest more energy and reduce energy consumption for relaying task bits.

Physical-Layer Security

During the offloading process in aerial MEC systems, potential eavesdroppers may intercept communication information, posing risks to data security and privacy [126]. To mitigate such risks, physical-layer security technology is widely applied, ensuring confidential data transmission without secret keys. In [127], a physical-layer security model for aerial MEC is proposed, where an AP employing full-duplex technique acts as both receiver for offloaded tasks from a single UAV and a jamming source to interfere with eavesdroppers. This prevents eavesdroppers from decoding transmitted messages. Energy-efficient computation offloading schemes are proposed for active and passive eavesdroppers to minimize UAV energy consumption while meeting security requirements. Similarly, in [128] and [129], a full-duplex UAV server with dual antennas receives offloading task bits from ground users while simultaneously sending jamming signals to eavesdropper UAVs. Non-offloading users also send jamming signals to further enhance security. Optimization of security capacity considers UAV positions, transmit power of UAVs and users, task offloading ratio, and user association. Additionally, [130] maximizes secure computation efficiency through a two-stage alternative optimization algorithm, jointly optimizing UAV trajectory and ground users' transmit power. Notably, implementations of physical-layer security in these works rely on full-duplex technique, where self-interference cancellation poses a challenge, as higher self-interference efficiency results in more residual self-interference power [129].

To overcome limitations of full-duplex technique, Y. Xu et al. [131] investigate security in aerial MEC systems with dual UAV deployment. One UAV assists ground users in computing tasks while the other acts as a jammer to suppress eavesdroppers. Minimum secure computing capacity is maximized for both Time Division Multiple Access (TDMA) and Non-Orthogonal Multiple Access (NOMA) schemes by optimizing communication and computation resources and UAV trajectories. Furthermore, [132] considers scenarios where an eavesdropper UAV intercepts offloading transmission from Mobile Devices (MDs) to computational AP without a jammer. Secrecy rates of offloading are derived, and the weighted sum of latency and energy consumption is minimized using Deep Q-Network (DQN) techniques.

RIS

In current aerial MEC optimization paradigms, the uncontrollable random radio environment is not typically considered in problem formulation. However, the concept of Reconfigurable Intelligent Surfaces (RIS) has recently emerged to construct smart radio environments. RIS consists of passive scattering elements, and by jointly controlling all scattering elements' phases, incident signal phases and angles can be tuned to add coherently and improve received signal power. RIS-assisted

ML-Driven Optimization for Aerial MEC

Traditionally, optimization for aerial Mobile Edge Computing (MEC) relies on methods like convex optimization, game theory, and heuristic algorithms. However, these methods often struggle with high dimensionality and require expert knowledge, making them less efficient for dynamic environments with numerous parameters. Machine Learning (ML) has emerged as a promising alternative, offering adaptive modeling and intelligent learning without manual intervention. ML algorithms can handle real-time decision-making in highly dynamic environments and large-scale networks with lower complexity. ML techniques encompass supervised learning, unsupervised learning, reinforcement learning (RL), deep learning (DL), deep reinforcement learning (DRL), and federated learning (FL) [6, 138]. Supervised and unsupervised learning are commonly used for computation offloading optimization, while RL, DRL, and FL are favored for resource allocation in aerial MEC systems [139, 140].

Reinforcement Learning

RL is particularly effective for decision-making in uncertain and stochastic environments, modeling problems as Markov Decision Processes (MDPs) [142]. RL involves an agent interacting with an environment to learn optimal actions based on rewards and punishments [141]. RL has been applied to optimize computation offloading in various scenarios. For example, in [144], MEC server deployment is optimized using RL algorithms to maximize long-term payoff. Similarly, [145] models computation offloading management of multiple UAVs as an MDP, optimizing system parameters selection. Additionally, [146] uses RL to determine offloading data amounts from UAVs to MEC servers in a non-cooperative game setting.

Q-learning is a popular RL technique and is widely used in the literature. For instance, [147] employs Q-learning to solve a dynamic pricing problem in edge computing services provided by UAVs. Similarly, [142] proposes a Q-learning-based computation offloading algorithm (QCOA) for a Multi-User Edge-Cloud network architecture, reducing task completion time and energy consumption. Moreover, [149] and [150] utilize single-agent and multi-agent Q-learning algorithms, respectively, to optimize UAV trajectory and task offloading ratio, and power and computation resource allocation for multi-UAV-enabled MEC networks.

Deep Reinforcement Learning

To overcome limitations of RL in large-scale systems with high-dimensional state and action spaces, Deep Reinforcement Learning (DRL) has been introduced, leveraging deep neural networks (DNNs) to expedite learning processes [151, 152]. DRL employs DNNs to estimate associated functions, resulting in faster learning and increased efficiency for complex systems [153]. In the optimization of aerial MEC systems, DRL techniques have shown promise in achieving faster convergence and improved performance compared to traditional RL methods.

In summary, ML-driven optimization techniques, including RL and DRL, offer efficient solutions for complex decision-making problems in aerial MEC systems. These techniques can adapt to dynamic environments and large-scale networks, providing near-optimal solutions with lower complexity and faster learning speed.

Open Problems and Future Directions

Despite the promising potential of UAV-enabled aerial MEC systems, several open problems remain to be addressed. This section discusses research opportunities and identifies key directions that warrant further investigation.

Space-Air-Ground Integrated MEC

Integrating satellite networks with UAV-enabled aerial MEC systems presents numerous challenges and opportunities. While satellites offer broad coverage and can enhance edge computing capabilities, they also introduce propagation loss and delay issues. Recent advancements in Low Earth Orbit (LEO) satellites have made them more economically viable, with reduced propagation delays. However, continuous channel state changes and frequent handovers due to high mobility pose optimization challenges. Operating UAVs and satellites in heterogeneous networks requires comprehensive mechanisms for cooperative communication, resource allocation, and protocol design to realize the benefits of integrated MEC systems.

Interference Management

The LoS-dominant air-ground channels in aerial MEC systems provide reliable connectivity but also cause strong air-ground interference, particularly in densely populated UAV networks. Addressing this challenge requires new techniques tailored to the dynamic and complex nature of aerial MEC. Distributed interference management schemes, such as Mean Field Game (MFG) and Reinforcement Learning (RL), offer self-organizing capabilities and can efficiently mitigate interference. Advanced physical-layer techniques like directional antennas and Full Dimension MIMO (FD-MIMO) also contribute to interference mitigation. However, challenges such as LoS direction tracking and joint optimization of resource allocation and UAV trajectory need further investigation.

ML-Driven Optimization for Aerial MEC

While Machine Learning (ML) shows promise for optimizing aerial MEC systems, several issues require attention. Multi-agent Deep Reinforcement Learning (DRL) is a popular approach, but coordination among agents remains challenging, especially in highly dynamic environments with limited radio resources. Efficient communication protocols for multi-agent coordination are needed to address these challenges. Additionally, ensuring security and privacy in information exchange among agents is crucial, requiring more efficient mechanisms for multi-agent learning.

Security Protection and Privacy Preserving

Security and privacy concerns in UAV-enabled aerial MEC systems demand robust solutions. Existing approaches address eavesdropping, DoS attacks, and trust evaluation, but challenges remain in ensuring secure data collection, validation, and storage. Lightweight authentication schemes and blockchain technology offer potential solutions, but comprehensive security mechanisms are needed to protect against diverse threats such as sensor spoofing and sleep deprivation attacks. Future research should focus on forecasting, protecting, and recovering aerial MEC systems from various security threats.

Wireless Charging for UAVs

Despite their appealing features, UAVs are constrained by limited onboard energy, typically resulting in short flight times. While battery swapping offers one solution, it can be time-consuming and disruptive. To address this, wireless charging technology for UAVs has garnered significant research attention. For example, Ansari et al. propose a novel architecture using free space optics (FSO) for energy and data transfer via laser beams. Additionally, for laser-powered UAVs with energy harvesting constraints, studies have investigated joint optimization of UAV trajectory and transmit power. Furthermore, UAVs equipped with sensors and photovoltaic (PV) cells can harvest solar energy, though the impact of PV cell area on charging performance requires investigation. However, practical deployment considerations such as atmospheric conditions and turbulence pose challenges that warrant further exploration.

Cache-Enabled Aerial MEC

Wireless caching, which proactively stores popular content at access points or storage devices, offers reduced content acquisition latency and alleviated network backhaul burdens. When integrated into aerial MEC, caching presents opportunities for performance enhancement, such as providing content to ground users and improving computing latency. However, challenges remain, including designing caching mechanisms to balance content popularity and finite storage capacity, and optimizing resource allocation considering communication, computing, and caching components along with UAV trajectory design. Addressing these challenges requires intensive research efforts.

Integration with Recent Promising Techniques

Advanced techniques such as radio-based sensing, Reconfigurable Intelligent Surfaces (RIS), and edge intelligence have emerged to support next-generation communications. While these techniques offer benefits such as privacy-preserving object detection and reduced latency, their direct applicability to aerial MEC systems is hindered by UAVs' unique features and operating environments. For example, the continually moving nature of UAVs may affect the effectiveness of RIS passive beamforming. Integrating these techniques into aerial MEC systems presents opportunities but also requires careful consideration of new challenges and potential benefits. While some research efforts have begun, further investigations are needed to fully exploit the potential benefits of these techniques in aerial MEC systems.

Conclusion

UAV-enabled aerial Mobile Edge Computing (MEC) holds immense promise for delivering ubiquitous and reliable MEC services across current and future wireless networks. However, realizing this potential requires ongoing efforts from both academia and industry. In this paper, we conducted a comprehensive survey of the research progress in aerial MEC.

We began by providing an overview of aerial MEC, covering network architecture and potential challenges. Next, we delved into the joint optimization of UAV trajectory, computation offloading, and resource allocation, considering UAVs' stringent Size, Weight, and Power (SWaP) constraints and controllable maneuverability.

We then reviewed strategies for UAV deployment, task scheduling, and load balancing, aimed at meeting users' dynamic requirements while minimizing deployment costs. Additionally, we explored the interplay between aerial MEC and other technologies like Wireless Power Transfer (WPT), Physical Layer Security (PLS), and Reconfigurable Intelligent Surfaces (RIS).

Furthermore, we highlighted the significant potential of Machine Learning (ML) in addressing complex control and resource allocation challenges in dynamic environments, discussing recent progress in ML-driven optimization for aerial MEC.

Lastly, we identified open problems and future directions in aerial MEC, including space-air-ground integrated MEC, interference management, ML-driven optimization, security protection, privacy preservation, wireless charging for UAVs, and cache-enabled aerial MEC. Additionally, we discussed the integration of aerial MEC with promising techniques such as radio-based sensing, RIS, and edge intelligence.

In summary, while UAV-enabled aerial MEC presents exciting opportunities, addressing its challenges and realizing its full potential will require continued collaboration and innovation across various domains.

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