A Review on Task Offloading and Resource Allocation in Aerial and Satellite-Assisted MEC Systems

Ayalneh Bitew Wondmagen
Department of Computer Science and Engineering
Chung-Ang University
Seoul, Republic of Korea
ayalneh@uclab.re.kr

Thwe Thwe Win
Department of Computer Science and Engineering
Chung-Ang University
Seoul, Republic of Korea
ttwin@uclab.re.kr

Dongwook Won
Department of Computer Science and Engineering
Chung-Ang University
Seoul, Republic of Korea
dwwon@uclab.re.kr

Jaemin Kim
Department of Computer Science and Engineering
Chung-Ang University
Seoul, Republic of Korea
jmkim@uclab.re.kr

Sungrae Cho
Department of Computer Science and Engineering
Chung-Ang University
Seoul, Republic of Korea
srcho@cau.ac.kr

***Abstract*—This review provides a detailed analysis of recent advancements in resource allocation and task offloading strategies to enhance energy efficiency in aerial and satellite-assisted MEC systems. With the increasing demand for low-latency and high-computation services from IoT devices, integrating terrestrial, aerial, and satellite networks has emerged as a promising solution to expand coverage and boost computational capabilities. However, these integrated MEC systems face significant challenges, including dynamic task arrival rates, limited and heterogeneous resources, and fluctuating communication quality across diverse network layers. The review categorizes existing research into three key domains: aerial-assisted MEC, satellite-assisted MEC, and combined aerial and satellite-assisted MEC systems. It examines various optimization approaches, including deep reinforcement learning (DRL), game theory, and hybrid algorithms, developed to address the complex problems of offloading and resource allocation in these environments. Furthermore, the review identifies open research challenges and potential future directions, such as advancing DRL techniques, to address current limitations. By offering insights into the state of the field, this review highlights research gaps and proposes pathways to improve the operational efficiency and energy management of aerial and satellite-assisted MEC systems.**

***Index Terms*—task offloading, MEC systems, resource allocation, UAV, HAP, satellite.**

I. Introduction

The rapid proliferation of data-intensive applications, such as autonomous vehicles, real-time surveillance, augmented reality, and Internet of Things (IoT) networks, has significantly increased the demand for low-latency, high-performance computing services. However, ground devices (GDs) are often constrained by limited battery life and computational capacity, making them inadequate for handling resource-intensive tasks. This constraint has created a critical need for effective task offloading solutions to ensure these devices can operate efficiently while maintaining high-quality service [1] [2].

MEC has emerged as a transformative paradigm to address this challenge. By bringing computational resources closer to end users, MEC systems reduce latency, enhance data processing efficiency, and improve the overall quality of service (QoS). Despite its potential, traditional ground-based MEC systems face notable limitations. These include inadequate coverage in remote or inaccessible locations, scalability challenges, and limited adaptability, particularly in dynamic or large-scale deployments. Additionally, natural disasters can disrupt ground-based facilities, rendering them unreliable. In such scenarios, establishing or repairing terrestrial communication systems is not only challenging but also prohibitively expensive [3].

To address these limitations, integrating aerial platforms and satellite networks into MEC architectures has gained significant traction. Aerial MEC systems, utilizing unmanned aerial vehicles (UAVs) and high-altitude platforms (HAPs), offer dynamic, on-demand resource allocation and extended coverage in both urban and remote areas [4]–[7]. Similarly, satellite-assisted MEC systems, particularly those employing LEO satellites, provide global connectivity and low-latency communication, making them ideal for isolated or underserved regions [8]–[10]. Together, these aerial and satellite systems complement ground-based MEC infrastructures, forming a heterogeneous architecture that offers unparalleled performance, flexibility, and scalability for next-generation networks.

Task offloading and resource allocation are critical for the seamless operation of these integrated MEC systems. Effective task offloading strategies determine how and where computa-

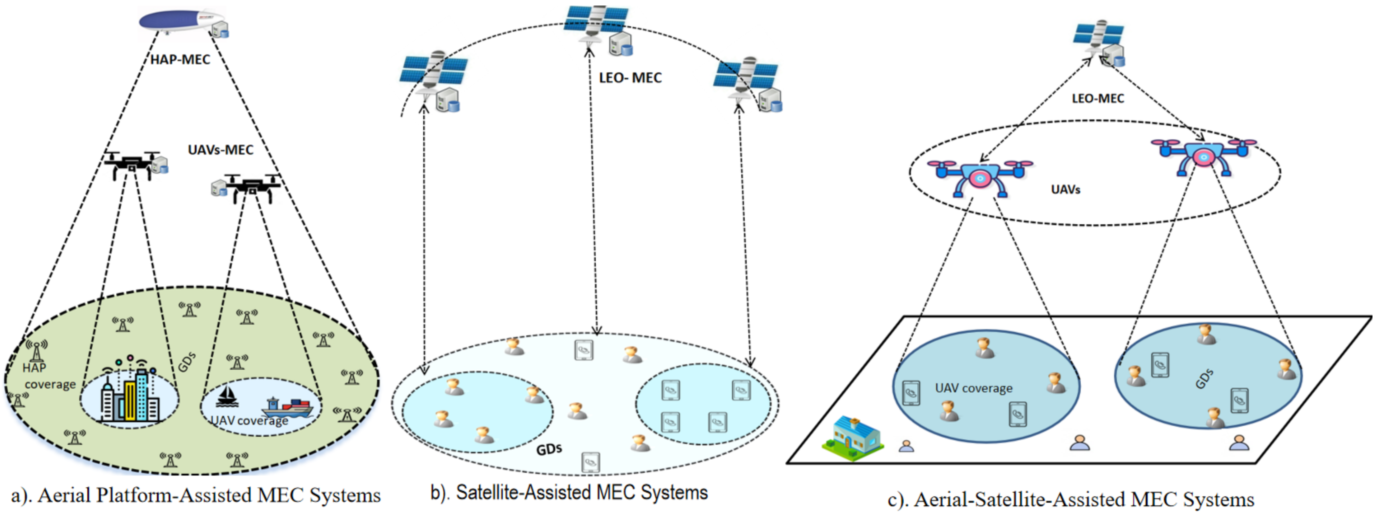

Fig. 1. Computational offloading and resource allocation in various network scenarios.

tional tasks are processed, balancing factors such as latency, energy consumption, and resource availability. Similarly, resource allocation mechanisms ensure the optimal distribution of computational, storage, and networking resources among competing tasks. However, the heterogeneous nature of aerial and satellite-assisted MEC systems introduces unique challenges, including resource heterogeneity, dynamic mobility, energy constraints, and unpredictable network conditions.

This paper presents a comprehensive review of task offloading and resource allocation techniques in aerial and satellite-assisted MEC systems. It explores state-of-the-art approaches, identifies key challenges and research gaps, and highlights emerging trends and future directions. By synthesizing existing research and providing critical insights, this study serves as a foundational reference for researchers and practitioners aiming to design and optimize MEC systems that leverage aerial and satellite platforms for enhanced performance and adaptability.

II. Resource Allocation and Task Offloading in Aerial and Satellite-Assisted MEC Systems

This section presents a structured taxonomy of recent advancements in resource allocation and task offloading in MEC systems, categorized into three primary network scenarios, as depicted in Fig. 1. First, aerial-assisted MEC systems involve GDs connecting with MEC-enabled aerial platforms including HAPs and UAVs to enhance computational and communication capabilities, addressing the limitations of ground-based devices. Second, satellite-assisted MEC systems leverage Low Earth Orbit (LEO) satellites to provide MEC services in remote or underserved regions, offering global coverage and low-latency communication where terrestrial infrastructure is insufficient or absent. Lastly, aerial-satellite-assisted MEC systems combine GDs, aerial platforms, and LEO satellites into a hybrid architecture, delivering extensive coverage, computational flexibility, and resource optimization for complex environments like disaster recovery and large-scale IoT deployments. While these approaches significantly enhance MEC capabilities, they introduce challenges such as resource heterogeneity, dynamic mobility, and energy constraints, requiring sophisticated algorithms for efficient resource allocation and task offloading. Following this taxonomy, we review existing research to identify key advancements, challenges, and opportunities in this evolving domain.

A. *Aerial-Assisted MEC Systems*

In this network architecture, MEC servers are deployed on aerial platforms such as UAVs and HAPs, creating a distributed computing environment that integrates GDs with these aerial platforms. Task offloading and resource allocation are central to optimizing system performance by determining the most efficient location for task processing—whether locally on GDs, on UAVs, or on HAPs. The goal is to achieve energy efficiency and high performance by considering factors such as task complexity, latency requirements, and available resources. A primary challenge is the efficient allocation of computational and communication resources to meet QoS demands.

Research in this domain can be categorized into two main areas: UAV-enabled MEC networks and integrated UAV and HAP-enabled MEC systems. In UAV-enabled MEC networks, UAVs serve as mobile MEC servers, addressing resource allocation and task offloading challenges through optimization techniques. For instance, in [5], researchers developed an optimization framework to minimize service delays and UAV power usage by jointly optimizing UAV positioning, communication, and resource allocation. Using successive convex approximation, they proposed an efficient algorithm to solve this complex problem. Similarly, [11] explored NOMA-UAV-assisted maritime communications, leveraging quasi-convex and coalition game approaches to manage computation offloading and resource allocation in complex environments. In another study [6], a hierarchical MEC-enabled UAV network was proposed, where UAV scouts and MEC-equipped UAVs collaborated with a base station controller, utilizing a soft actor-critic (SAC) algorithm to adapt to dynamic conditions. Moreover, [7] introduced a three-layer architecture combining vehicle fog computing, UAVs, and edge layers for post-disaster scenarios, employing game-theoretic and evolutionary algorithms for resource optimization. Lastly, [12] developed the DRTORA scheme, which uses DRL to optimize UAV trajectories, task offloading, and time allocation, ensuring secure and efficient computational performance under various constraints.

In more complex scenarios involving both UAVs and HAPs, the focus shifts to leveraging the broader coverage and higher computational capacity of HAPs, albeit with higher latency compared to UAVs. Studies such as [3] explored how MEC-equipped UAVs can partially offload tasks to HAPs, optimizing energy consumption while meeting QoS requirements. Stochastic optimization and game-theoretic methods were employed to manage resource allocation and task offloading. Furthermore, advanced frameworks like Swarming-behavior-integrated Multiagent gated recurrent unit-based Actor and multihead Attention-based Critic (SMA-GAC), introduced in [4], utilized machine learning techniques, including swarm intelligence and DRL, to solve joint task offloading and resource allocation problems under multiple constraints, enhancing overall system performance. These integrated systems capitalize on the complementary strengths of UAVs and HAPs, balancing computational demands, energy efficiency, and QoS to address real-world challenges effectively. However, the scalability challenge of the SMA-GAC framework, as its computational complexity increases significantly with the number of UAVs and ground devices, potentially hindering real-world applicability in larger networks.

B. Satellite-Assisted MEC Systems

Satellite-assisted MEC systems aim to bring computation closer to end-users by equipping satellites with edge computing capabilities. In these systems, computation offloading involves transferring tasks from IoT devices to satellites for low-latency processing. However, this process presents significant challenges due to the dynamic and unpredictable nature of satellite orbits. Satellites move rapidly relative to the Earth and each other, affecting connectivity, resource availability, and the management of inter-satellite links (ISLs). These dynamic conditions necessitate efficient resource allocation to ensure stable communication, balanced task distribution, and energy efficiency.

Key challenges include managing limited bandwidth and power resources, balancing workloads across multiple satellites and ISLs, and minimizing latency and energy consumption. Offloading decisions must dynamically adapt to varying task requirements, such as data size, computational needs, and deadlines, to prevent overloading individual satellites or communication links. Addressing these challenges requires intelligent algorithms that can optimize resource allocation and task routing in real time, accounting for satellite movement and network conditions.

Several advanced approaches have been proposed to tackle these issues. For example, the hierarchical dynamic resource allocation (HDRA) algorithm [13] uses a breadth-first search to select optimal satellites and routing paths, followed by a greedy method for offloading ratio and resource allocation. Another study [14] introduced a joint optimization algorithm to minimize energy consumption by optimizing offloading decisions and computing resource allocation, effectively decoupling complex variables for optimal solutions. Similarly, [15] proposed a two-layered framework for terrestrial-satellite IoT using LEO satellites, minimizing energy consumption with the energy-efficient computation offloading and resource allocation algorithm (E-CORA), leveraging Lagrangian dual decomposition and sequential fractional programming.

In addition, advanced machine learning techniques have been employed to enhance decision-making in satellite edge computing. A Seq2Seq-based decision generation algorithm combined with DRL was introduced in [16] to optimize offloading strategies for intensive tasks, accounting for inter-satellite transmission and computation delays. Another study [17] presented the DRLCO algorithm, integrating DRL with traditional optimization methods to assist ground users and LEO satellites in dynamic network environments. A caching-assisted computational offloading and resource optimization approach [18] further improved offloading strategies by incorporating caching architectures and DRL to maximize cache utility.

Moreover, [19] proposed a novel LEO-assisted Open RAN architecture, integrating a near real-time RIC (Radio Access Network Intelligence Controller) in LEO satellites and a non-real-time RIC in terrestrial networks. This framework jointly optimizes offloading decisions, computing resource allocation, and cache updates, minimizing energy consumption while adhering to communication, computing, and cache constraints. The authors employed the deep deterministic policy gradient method to model and optimize these decisions, significantly enhancing network performance. The main limitation of this paper is the lack of consideration for the energy and computational overhead associated with inter-satellite communication and coordination within the proposed LEO-assisted Open RAN (LO-RAN) architecture, which may impact scalability and real-world feasibility.

These studies collectively highlight the rapid advancements in satellite-assisted MEC systems. By leveraging innovative algorithms, optimization techniques, and machine learning models, researchers are addressing the complex challenges of resource allocation and task offloading in dynamic, multi-layered satellite networks, paving the way for more efficient and reliable satellite edge computing solutions.

C. Aerial-Satellite-Assisted MEC Systems

Aerial-satellite-assisted MEC systems integrate UAVs, MEC-enabled satellites, and GDs to create a unified computing framework that optimizes energy efficiency while meeting performance requirements such as low latency and high reliability. This approach leverages the strengths of each layer: MEC-

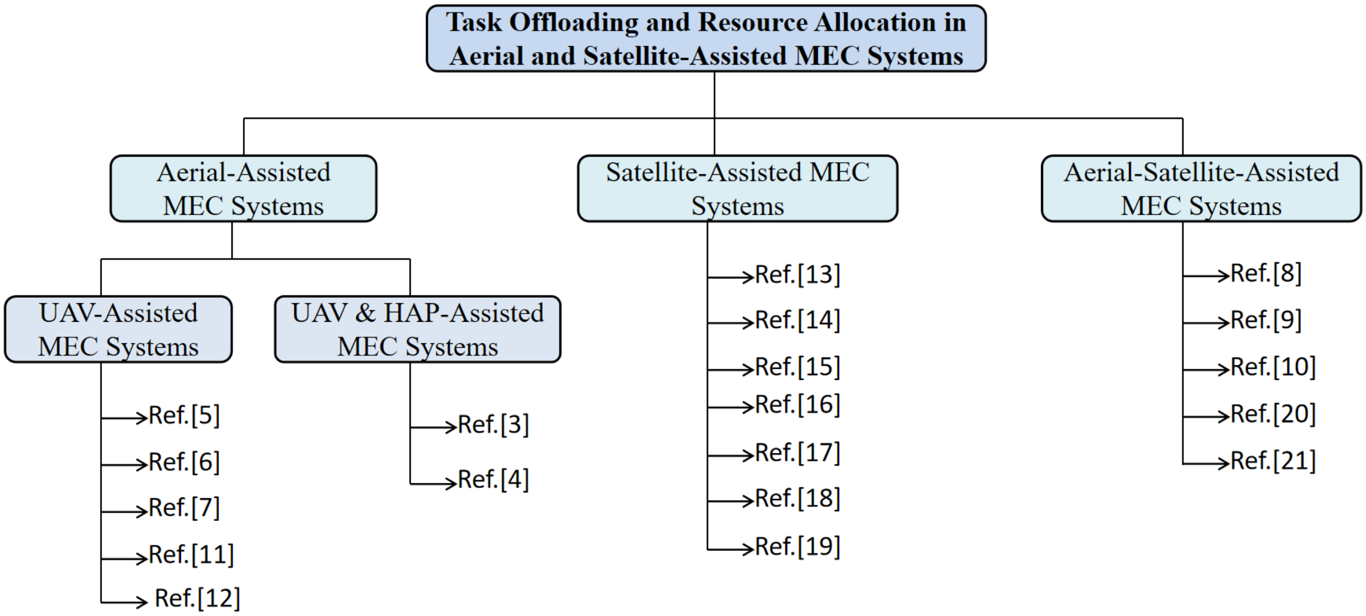

Fig. 2. Taxonomy of job offloading and resource assignment Different Network Scenarios.

enabled satellites provide wide-area coverage and substantial computational resources, UAVs offer flexibility and rapid response capabilities, and GDs benefit from the ability to offload tasks to these aerial and space-based platforms. The primary challenge in such systems is dynamically determining the optimal task processing locations and efficiently allocating computing and communication resources across these heterogeneous platforms.

In [8], a method was proposed to minimize energy consumption and task completion delays in SA-MEC (space-air MEC) systems using a BCD algorithm (block coordinate descent). This approach dynamically allocates tasks to the most appropriate edge server by considering its location and resource availability, thereby ensuring energy efficiency while meeting task deadlines. Similarly, [9] introduced a DRL-based solution for joint optimization of resource allocation and task offloading in hybrid cloud and MEC scenarios within space-air-ground integrated networks. This system, incorporating satellites, UAVs, and cloud platforms, employed a multi-agent DRL algorithm to optimize resource usage and reduce latency and energy consumption.

In [10], the focus was on minimizing total energy consumption in ground-air-space integrated MEC networks. This was achieved by jointly optimizing ground user equipment association, multi-user MIMO transmit precoding, computational task distribution, and resource management. The complex non-convex optimization problem was decomposed into four subproblems, solved iteratively using techniques such as quadratic transform-based fractional programming and weighted minimum mean-squared error methods. In [20], a joint task offloading and resource allocation strategy (JTRSS) was proposed for space-air-ground vehicular networks. The strategy expanded task offloading options for vehicles by integrating air and space networks and deploying edge servers. Using maximum rate matching for channel allocation, the Lagrangian multiplier method for computational resource allocation, and a differential fusion cuckoo search algorithm for optimal offloading decisions, JTRSS minimized system costs while improving computational performance.

Further innovations include the work in [21], where a network model was developed to enable resource-constrained energy-harvesting UAVs (EH-UAVs) to offload tasks to LEO satellite-MEC server. The EH-UAVs periodically collected data from IoT devices and generated tasks for processing. A joint optimization problem involving selection of LEO satellite, offloading partial task, and allocation of transmission power was formulated to optimize service satisfaction and minimize energy consumption within constraints such as connectivity duration, task deadlines, and energy availability. Due to the problem's non-convex and dynamic nature, it was restructured as RL task and solved using the MDC²-DRL (mixed discrete-continuous control DRL) algorithm, incorporating action shaping for efficient decision-making. The main limitation of this paper is the lack of consideration for the computational and energy overhead of the intermittent and stochastic energy harvesting process, which could affect the stability and practicality of the proposed network (LEO-MEC-assisted EH-UAV network) under real-world conditions

These studies collectively highlight the diverse strategies employed to optimize task offloading and resource allocation in ground-air-satellite integrated MEC systems. By addressing energy efficiency, latency reduction, and resource utilization, these advanced algorithms are tailored to the unique characteristics and challenges of these multi-layered network environments, paving the way for enhanced system performance and scalability.

III. Challenges And Open Research Issues

Energy-efficient resource allocation and task offloading in aerial and satellite-assisted MEC systems face significant challenges due to the complexity of hybrid networks. Key issues include optimizing resource allocation across terrestrial, aerial, and satellite layers, each with diverse energy constraints and fluctuating network conditions. Maintaining low latency while accounting for the mobility of UAVs and HAPs further complicates the process. Seamless interoperability between these layers, alongside addressing security and privacy concerns, is crucial for effective implementation.

Open research directions focus on developing advanced algorithms capable of adapting to dynamic environments, managing energy efficiently, and optimizing real-time task scheduling. DRL techniques, such as Proximal Policy Optimization (PPO) and Deep Q-Learning (DQN), have shown promise in UAV-enabled MEC networks. These techniques enable dynamic adjustments of UAV trajectories, task offloading, and resource allocation based on changing network conditions. By considering factors such as UAV energy, network traffic, and user mobility, DRL approaches can enhance task scheduling, reduce energy consumption, and improve system efficiency.

However, handling the large-scale, multi-agent nature of these networks while maintaining energy efficiency remains a critical challenge. Advancing machine learning and DRL techniques to address these complexities is essential for the realization of robust and scalable MEC solutions in hybrid networks.

IV. Conclusion

In this paper, we reviewed and discussed energy-efficient resource allocation and task offloading across various network scenarios. We began by presenting a taxonomy of existing research, categorizing studies into three main areas: task offloading and resource allocation in Ground-Air enabled MEC systems, Ground-Satellite enabled MEC systems, and Ground-Air-Satellite integrated MEC systems. For each category, we provided a detailed review and discussion of relevant works. Lastly, we highlighted the current research challenges in these domains and identified open research issues that merit further investigation.

ACKNOWLEDGMENT

This research was supported by the MSIT(Ministry of Science and ICT), Korea, under the ITRC(Information Technology Research Center) support program(IITP-2025-RS-2024-00436887) supervised by the IITP(Institute for Information & Communications Technology Planning & Evaluation).

References

[1] X. Cao, G. Zhu, J. Xu, and S. Cui, "Transmission power control for over-the-air federated averaging at network edge," *IEEE Journal on Selected Areas in Communications*, vol. 40, no. 5, pp. 1571–1586, 2022.

[2] F. Liu, J. Huang, and X. Wang, "Joint task offloading and resource allocation for device-edge-cloud collaboration with subtask dependencies," *IEEE Transactions on Cloud Computing*, vol. 11, no. 3, pp. 3027–3039, 2023.

[3] Y. Chen, K. Li, Y. Wu, J. Huang, and L. Zhao, "Energy efficient task offloading and resource allocation in air-ground integrated mec systems: A distributed online approach," *IEEE Transactions on Mobile Computing*, 2023.

[4] M. M. Alam and S. Moh, "Joint optimization of trajectory control, task offloading, and resource allocation in air–ground integrated networks," *IEEE Internet of Things Journal*, 2024.

[5] Z. Yu, Y. Gong, S. Gong, and Y. Guo, "Joint task offloading and resource allocation in uav-enabled mobile edge computing," *IEEE Internet of Things Journal*, vol. 7, no. 4, pp. 3147–3159, 2020.

[6] S. Akter, D. V. A. Duong, D.-Y. Kim, and S. Yoon, "Task offloading and resource allocation in uav-aided emergency response operations via soft actor critic," *IEEE Access*, 2024.

[7] G. Sun, L. He, Z. Sun, Q. Wu, S. Liang, J. Li, D. Niyato, and V. C. Leung, "Joint task offloading and resource allocation in aerial-terrestrial uav networks with edge and fog computing for post-disaster rescue," *IEEE Transactions on Mobile Computing*, 2024.

[8] M. Barakat, R. A. Saeed, S. Edam, E. S. Ali, M. M. Saeed, M. S. Elbasheir, A. A. Elnaim, and A. Babeker, "Energy-aware task completion delay optimization of space-aerial enabled mec system," in *2024 IEEE 4th International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*. IEEE, 2024, pp. 440–445.

[9] C. Huang, G. Chen, P. Xiao, Y. Xiao, Z. Han, and J. A. Chambers, "Joint offloading and resource allocation for hybrid cloud and edge computing in sagins: A decision assisted hybrid action space deep reinforcement learning approach," *IEEE Journal on Selected Areas in Communications*, 2024.

[10] C. Ding, J.-B. Wang, H. Zhang, M. Lin, and G. Y. Li, "Joint optimization of transmission and computation resources for satellite and high altitude platform assisted edge computing," *IEEE Transactions on Wireless Communications*, vol. 21, no. 2, pp. 1362–1377, 2021.

[11] T. Lyu, H. Xu, F. Liu, M. Li, L. Li, and Z. Han, "Computing offloading and resource allocation of noma based uav emergency communication in the marine internet of thing," *IEEE Internet of Things Journal*, 2023.

[12] Y. Gao, Y. Ding, Y. Wang, W. Lu, Y. Guo, P. Wang, and J. Cao, "Deep reinforcement learning-based trajectory optimization and resource allocation for secure uav-enabled mec networks," in *IEEE INFOCOM 2024-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*. IEEE, 2024, pp. 01–05.

[13] X. Gao, Y. Hu, Y. Shao, H. Zhang, Y. Liu, R. Liu, and J. Zhang, "Hierarchical dynamic resource allocation for computation offloading in leo satellite networks," *IEEE Internet of Things Journal*, 2024.

[14] F. Dong, Y. Zhang, Q. Tang, and K. Wei, "Joint optimization of computation offloading and resource allocation for leo satellite edge computing networks," in *2024 5th Information Communication Technologies Conference (ICTC)*. IEEE, 2024, pp. 199–203.

[15] Z. Song, Y. Hao, Y. Liu, and X. Sun, "Energy-efficient multiaccess edge computing for terrestrial-satellite internet of things," *IEEE Internet of Things Journal*, vol. 8, no. 18, pp. 14 202–14 218, 2021.

[16] Y. Wang, F. Chai, Q. Zhang, Y. Li, M. Sun, D. Sun, F. Tian, F. Wang, Y. Wang, Q. Tian *et al.*, "Intensive tasks offloading decision algorithms in satellite edge computing systems," in *2024 22nd International Conference on Optical Communications and Networks (ICOCN)*. IEEE, 2024, pp. 1–3.

[17] Q. Tang, Z. Fei, B. Li, H. Yu, Q. Cui, J. Zhang, and Z. Han, "Stochastic computation offloading for leo satellite edge computing networks: A learning-based approach," *IEEE Internet of Things Journal*, 2023.

[18] F. Chai, Q. Zhang, X. Xin, Y. Wang, Y. Li, M. Sun, D. Sun, F. Tian, Q. Tian, Y. Wang *et al.*, "Cache-assisted task offloading and resource optimization for leo network," in *2024 22nd International Conference on Optical Communications and Networks (ICOCN)*. IEEE, 2024, pp. 1–3.

[19] Q. Wang, W. Qi, J. Ling, J. Zong, Y. Shen, and D. Liu, "Energy-efficient resource allocation in leo-assisted open ran architecture towards 6g," in *2024 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*. IEEE, 2024, pp. 1–6.

[20] Y. Gang, Y. Zhang, and Z. Zhuo, "Joint task offloading and resource allocation strategy for space-air-ground integrated vehicular networks," *Tsinghua Science and Technology*, 2024.

[21] D. S. Lakew, A.-T. Tran, N.-N. Dao, and S. Cho, "Intelligent self-optimization for task offloading in leo-mec-assisted energy-harvesting-uav systems," *IEEE Transactions on Network Science and Engineering*, 2024.