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Mobile Edge Computing for 6G Non-Terrestrial Networks: A Survey

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ABSTRACT

In order to provide high-speed, low-latency connectivity, 6G technology emerges as a promising solution, offering terahertz-frequency operation, ultra-low latency, and seamless integration with cutting-edge technologies like artificial intelligence, quantum computing and blockchain. In order to extend connectivity to remote regions, the integration of non-terrestrial networks (NTNs), including satellites and unmanned aerial vehicles (UAVs), with 6G networks has become imperative. Moreover, the integration of mobile edge computing (MEC) into 6G terrestrial networks (TNs) and NTNs plays a crucial role in minimizing latency, optimizing backhaul traffic, and enhancing user experience by bringing computational resources closer to end-users. To this end, this paper presents various deployment scenarios for MEC servers, including base stations, UAVs, satellites, and gateways, and explores different user access scenarios for both TNs and NTNs. By providing a comprehensive overview of 6G TNs and NTNs, and their integration with MEC, this paper addresses existing research, tackles challenges, and outlines future directions to propel wireless communication and computing paradigms forward.

Key Words : 6G communication, Satellite communication, Mobile edge computing (MEC), Non-terrestrial networks (NTN)

Ⅰ. Introduction

In an increasingly connected world characterized by the proliferation of internet of things (IoT) devices, autonomous systems, and immersive multimedia applications, the demand for high-speed, low-latency connectivity has never been greater [1]. As existing wireless networks strain to accommodate the burgeoning data traffic generated by a multitude of devices and services, the need for a transformative leap in communication technology becomes apparent. As the 5th generation (5G) networks continue to mature and proliferate, the spotlight is now shifting towards the development of the 6th generation (6G), the next frontier in wireless communication. Envisioned as a paradigm shift beyond 5G, 6G aims to deliver unprecedented levels of performance, reliability, and intelligence, ushering in an era of ubiquitous connectivity and immersive experiences. Key features of 6G networks include terahertz-frequency operation, ultra-low latency, massive device connectivity, and seamless integration with emerging technologies such as artificial intelligence (AI), blockchain, and edge computing.

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Table 1. Summary of state-of-the-art contributions related to NTNs and MEC.

Category	Ref.	Key contributions
NTN	[16]	Propose machine learning techniques for managing NTN connectivity as well as to improve service performance
	[17]	Address challenges such as quality of experience, computation offloading, task scheduling, mobility management, and fault recovery, focusing mainly on satellite relays
	[21]	Discuss 3GPP's roadmap for NTN standardization, focusing on energy-efficient internet of remote things environment
MEC	[68]	Propose the SDN-based MEC system to reduce energy consumption and latency in Industry 4.0
	[70]	Propose the reliability-aware virtual network function instance provisioning in MEC to maximize network throughput
	[73]	Explore optimal resource allocation in information-centric wireless networks using MEC and D2D communication to alleviate core network congestion
	[75]	Propose an algorithm to solve the problem of maximizing average revenue, balancing revenue, and delay
UAV-aided network	[81]	Propose a double deep double Q-learning algorithm for air-ground integrated networks, optimizing computation offloading and relay communication for UAVs, emergence vehicle users, and ground sensor nodes in emergency scenarios
	[84]	Propose a hybrid data aggregation method for large IoT networks using both multi-hop routing and UAVs
	[87]	Propose a MEC-driven UAV inspection scheme for wind turbines in remote areas to improve costs efficiency
NTN+ MEC	[15]	Propose a process-oriented framework that optimizes communication and MEC in a time-division manner
	[79]	Consider the latency and energy optimization in MEC-enhanced Satellite-IoT networks
	[80]	Propose the satellite mobile edge computing to improve QoS in high-speed satellite-terrestrial networks

Additionally, the integration of non-terrestrial networks (NTN) with 6G, encompassing satellite communication systems and unmanned aerial vehicles (UAVs), emerges as a viable solution to extend connectivity to remote and underserved regions[2,3]. With the ability to transcend geographical barriers and deliver ubiquitous coverage, NTNs complement terrestrial infrastructure and play a crucial role in bridging the digital divide. In particular, satellite communication has been recognized for its potential to deliver high-speed internet access globally at a fraction of the cost associated with traditional infrastructure. The evolution from geostationary earth orbit (GEO) to low earth orbit (LEO) satellite networks marks a significant advancement, with projects like OneWeb, Telesat, and Starlink leading the charge toward achieving lower latency and reduced path loss. Despite the advantages offered by satellite networks, challenges such as slower data transmission speeds and higher latency compared to terrestrial networks persist, posing hurdles for latency-sensitive and computation-intensive IoT applications.

In this context, mobile edge computing (MEC) has emerged as a pivotal paradigm, poised to revolutionize the way network services are delivered and consumed[4]. By leveraging computational resources at the network edge, MEC promises to enhance latency-sensitive applications, optimize network traffic, and enable novel use cases spanning various domains, including healthcare[5-9], transportation and smart cities[10-14]. The integration of MEC into next-generation wireless networks, particularly 6G, holds tremendous potential to unlock new frontiers in connectivity and enable unprecedented levels of innovation[15].

Against this backdrop, this survey paper aims to provide a comprehensive overview of the state-of-the-art in NTNs, MEC, and the integration of MEC into 6G NTNs. By synthesizing existing re-

Table 2. Comparisons between satellite communication systems.

	LEO satellite	GEO satellite	Starlink satellite
Bandwidth	UHF and Ka band	C, Ku, Ka band	Up to 240 MHz
Altitude	400~1500km	More than 36,000km	550~570km
Latency	Tens to 100ms	More than 500ms	20ms~40ms
Coverage	1000km	15000km	
Types	Polar, Inclined	Stationary relative to the user	

search efforts, identifying key challenges, and outlining future directions, this paper seeks to offer valuable insights into the ongoing evolution of wireless communication and computing paradigms, laying the foundation for future research endeavors and technological advancements in the field. Table 1 presents the summary of state-of-the-art contributions related to NTNs and MEC.

The structure of the paper is outlined as follows: Section II provides an introduction to NTN, discussing its significance, challenges, and current research developments. In Section III, the concept of MEC is introduced, elucidating its necessity, diverse applications, and the underlying enabling technologies. Section IV considers various scenarios illustrating the integration of MEC with 6G NTNs. Finally, concluding remarks are presented in Section V, summarizing the key findings and highlighting potential future directions.

Ⅱ. 6G Non-Terrestrial Networks

6G technologies are poised to revolutionize the wireless ecosystem by enabling services through both terrestrial and non-terrestrial means. NTNs emerge as a pivotal innovation, designed to deliver connectivity

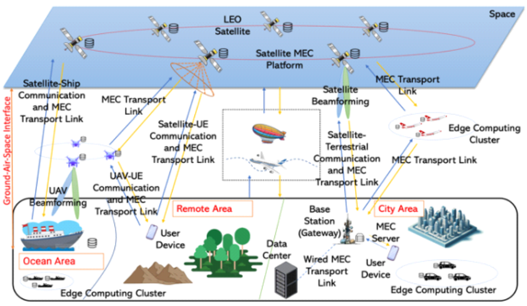

Fig. 1. 6G non-terrestrial networks.

across the globe, including in regions where traditional terrestrial networks (TNs) cannot reach. Fig. 1 illustrates the concept of 6G NTNs that combine ground, air, and space components, embodying an integrated ground-air-space network structure. This concept aims to combine various communication platforms and technologies to provide extensive coverage, high data transmission speeds, minimize latency, and enhance network reliability. Next, we will divide the explanation of NTNs into two parts, with the first part focusing on the characteristics of 6G NTNs and the second part discussing 6G NTN requirements and current development status.

2.1 Characteristics and Challenges

Driven by shared radio technology, the integration of NTNs and TNs is expected to form a cohesive and widespread wireless system with the following advantages[16-18]:

- **Global coverage**: It can provide stable communication services in all areas (rural areas with underdeveloped communication networks, mountainous areas, and oceans).
- **High reliability and Low Latency**: The network enhances reliability and minimizes latency by diversifying network choices at different levels.
- **Flexibility and scalability**: It provides a flexible and scalable network structure that can be adapted to various communication needs and environments by changing the choice of networks; moreover, it can change offloading decisions to control resource allocation.
- **Disaster response**: In the event of a disaster, communications can continue over air and space networks even if the terrestrial infrastructure is damaged.

However, NTNs encounter several challenges, such as rapid mobility of satellites or UAVs, long propagation distances, and the absence of precise channel and uncertainty models for non-terrestrial objects.

To address these challenges, comprehensive modeling for satellite or UAV mobility[19], along with NTN channel models, uncertainty models for non-terrestrial objects, and objective functions tailored to NTN networks should be firstly developed, with a focus on mitigating angle or phase errors and accounting for user terminal mobility. Additionally, the exploration of beamforming without channel state information at the transmitter side (CSIT) seeks to adapt to the dynamic nature of NTN environments, leveraging decentralized precoding schemes and deep learning to predict optimal beam configurations without explicit channel state information (CSI)[20-22]. Meanwhile, the concept of RIS in 6G networks introduces the ability to intelligently manipulate signal propagation, enhancing the communication link between satellites and ground terminals through passive reflection[23-25]. The future of satellite systems also hinges on the efficient utilization of spectrum resources, exploring scenarios where terrestrial and satellite systems can share spectrum or expand network capabilities through cooperation[26].

2.2 Requirements and Current Status

For 6G NTNs, several requirements have been proposed[1,3,27], which require a new network structure and enhanced delay and data rate demands.

In the architecture of 6G NTNs, as proposed in the International Telecommunication Union (ITU) 6G white paper[1], there is a significant increase in integration between NTN compared to 5G NTNs. Ground platforms will also extend through mobile base stations (BSs), which can be achieved through clusters formed by vehicles, ships, and other means. These mobile BSs can directly provide connectivity. In the atmosphere, clusters such as drones, aircraft, and air taxis can be anticipated, used for delivery services among others. Additionally, in space, the development of various traditional 5G satellites, such as LEO and GEO satellites, along with advancements in microsatellites and nanosatellites, also can play a crucial role[2].

The scalability of radio frequency (RF) carrier bandwidth is essential for facilitating diverse deployments of wireless access technology in non-terrestrial systems. 3GPP delineates LTE for a carrier bandwidth ranging from 1.3 to 20 MHz, and 5G NR for a bandwidth spanning from 5 to 100 MHz in frequency range 1 (FR1) and from 50 to 400 MHz in frequency range 2 (FR2). The white paper[3] points out that, ground operators' infrastructure can be shared for satellite access to user equipment (UE) located in different regions. At the same time, resource utilization optimization/sharing in hybrid systems (6G NTNs and 5G NTNs) should be maintained even when using non-6G (non-3GPP) NTNs.

The development of 6G NTN technology is not only led by governments and operators but also actively involves some enterprises. The most notable of these is the SpaceX's Starlink project, where Table 1 states the key features of Starlink satellites compared with conventional LEO and GEO satellites. By the end of 2023, Starlink had launched over 2,000 satellites, with plans to further expand to tens of thousands in the coming years. This vast satellite network aims to provide high-speed internet connectivity globally, especially in remote and underserved areas. Additionally, other companies such as Amazon's Project Kuiper and the UK's OneWeb are also actively deploying similar satellite networks. The participation of these enterprises will bring more innovation and competition to the development of 6G NTN technologies, laying a solid foundation for the global proliferation of 6G NTNs.

Ⅲ. Mobile Edge Computing

In this section, we discuss MEC, which is playing a pivotal role in reshaping the landscape of wireless communication networks. It revolutionizes the network architecture by bringing the computational resources closer to the users, unlocking unprecedented levels of performance and efficiency. Here, we present its fundamental principles, diverse applications, and the underlying technologies driving its evolution.

The evolution of wireless communication technology is ushering in a new era of networks characterized

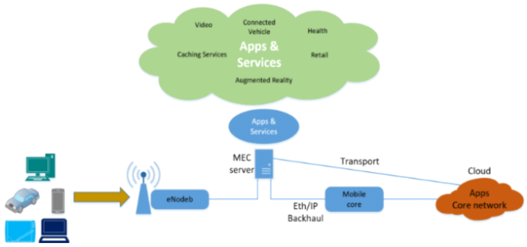

Fig. 2. Mobile edge computing systems.

by ubiquitous connectivity, linking everyone and everything, including machines, objects, and devices. These next-generation networks are poised to deliver several key advancements, including higher multi-Gbps peak data speeds, ultra-low latency, enhanced reliability, massive network capacity, increased availability, and a more consistent user experience for a broader user base.

Despite these advancements, such as 5G, offering speeds approximately 20 times faster than LTE, the average user may not always experience a significant improvement in their connectivity experience. This is because data must travel to the core network, which is often distant from the end user. To address this challenge, MEC has emerged as a promising solution[4]. By integrating into the backhaul network, MEC brings data processing closer to the user as depicted in Fig. 2, resulting in reduced latency, backhaul traffic, enhanced network efficiency, improved user experience, and greater network resilience. MEC enables diverse applications to fully leverage the capabilities of 5G/6G technologies, including but not limited to healthcare, industrial automation, intelligent transportation systems, and virtual reality.

3.1 MEC Applications

3.1.1 Healthcare

A rapid growth in IoT has resulted in new technologies like internet of medical things (IoMT)[28] and wireless body area networks[29] are used in healthcare for data collection, monitoring, and analysis. IoT devices have limited computation power, battery and storage capabilities. Therefore, leveraging MEC enhances the capabilities of these technologies by utilizing its communication and computation capabilities at the network edge, thereby enabling applications like real-time patient monitoring[30], athlete fitness tracking [31], and remote surgery[32]. Efforts to enable real-time monitoring have spurred research into optimizing computation offloading strategies aimed at minimizing latency[33-35]. Additionally, considerable attention has been devoted to reducing the energy consumption of MEC-based IoMT systems, given the resource-constrained nature of IoT devices[36,37]. Moreover, the transmission of patient data to MEC servers introduces significant concerns regarding security and privacy, prompting extensive research into safeguarding sensitive healthcare information[38].

3.1.2 Industrial automation

MEC also offers substantial improvements to industrial automation through its provision of ultra-low latency, high bandwidth, and localized processing capabilities. This facilitates predictive maintenance[39], quality control[40], inventory and product tracking[41], and use of AI in industrial processes[42], leading to enhanced efficiency, productivity, and safety. The primary consideration when implementing MEC systems revolves around determining the optimal locations for deploying MEC servers, prompting a plethora of studies aimed at identifying effective deployment strategies[43,44]. Since Industrial-IoT[45] is playing a crucial rule in industrial automation through deployment of sensors, actuators and connected devices, this generates a huge amount of data, posing challenges regarding how and where to offload the data effectively. To address this challenge, research has focused on developing computation offloading strategies tailored to different objectives, such as latency minimization[46], energy minimization[47] and load balancing[48]. However, since data needs to be offloaded to the MEC server from a diverse set of devices, several security and privacy issues can arise such as data breaches and unauthorized access. Consequently, research efforts have been directed towards mitigating these risks and ensuring the security of MEC-enabled industrial automation systems[49,50].

3.1.3 Smart driving vehicles

Smart driving vehicles (SDVs) utilize MEC to navigate complex road conditions, enabling real-time information sharing among drivers to prevent accidents and facilitate autonomous vehicle operation. Foundation of MEC-enabled SDV rests upon the strategic placement of computing resources in order to minimize placement costs and enhancing communication speeds. Dimensioning and layout planning emerge as crucial endeavors in [12], shedding light on the optimization of 5G-based vehicular edge computing networks. Furthermore, networking between autonomous vehicles plays an important role in safer roads. In [10], a framework is proposed for intelligent networking among autonomous vehicles with MEC support, updating driving models for evolving environments. Beyond vehicle-to-vehicle communication, the interactions encompassing vehicle-to-everything (V2X) and vehicle-to-infrastructure (V2I) communications hold significant importance, underscoring the necessity of scheduling these diverse communication channels as a critical issue. The work in [11] presents a hybrid transmission and reputation management system, leveraging 5G V2X technology and vehicle-to-vehicle and V2I scheduling algorithms to enhance reliability in SDVs with MEC. Amidst the flurry of technological advancements, concerns regarding privacy and security loom large. Recognizing the need for robust authentication frameworks, [13] introduces a pioneering privacy-preserving authentication framework tailored for secure communication in 5G-enabled vehicular networks. Similarly, [14] proposes a software-defined cooperative data sharing architecture, bolstering communication efficiency within 5G-enabled vehicular ad hoc networks and fostering a culture of seamless data exchange among SDVs.

3.1.4 Virtual reality

Edge server computation offloading offers a promising solution for reducing the bulk of virtual reality glasses, thereby enhancing the user experience in virtual reality, augmented reality, and mixed reality applications. Cache and computing resource deployment have been studied for 5G networks in [51] to optimize content distribution efficiency and minimize network transmission delay for augmented reality applications. Furthermore, the intersection of virtual reality and AI necessitates robust computational capabilities and ample storage, making MEC an ideal solution. The work in [52] presents an edge-based collaborative object recognition solution for mobile Web augmented reality in the 5G era, employing a deep neural network partitioning and adaptive computation scheduling to balance user experience and computing cost, validated through 5G trial network experiments. Recognizing the pivotal role of MEC servers in processing, motion-aware communication planning emerges as another significant challenge to enhance the quality of experience (QoE) for end-users[53,54]. Addressing this, [54] proposes an edge-assisted multi-user collaborative framework for mobile web AR, featuring efficient communication planning and motion-aware key frame selection mechanisms, validated through real-world 5G network experiments.

3.2 Goals of MEC Computation Offloading

3.2.1 Minimization of latency

Efforts in MEC computation offloading studies aim to reduce the delay between task generation and execution by leveraging proximity to end-users or devices. This includes exploring techniques such as edge caching, task partitioning, and predictive offloading[5558].

In [55], joint communication and computation resource allocation are explored to minimize the weighted sum-delay in cloud-edge collaboration systems, offering optimal task splitting strategies. Additionally, [56] introduces a block coordinate descent based task offloading scheme in an intelligent reflecting surface enabled MEC system, aiming to minimize computation latency while adhering to practical constraints. Moreover, [57] presents a joint partial offloading and resource allocation scheme tailored for D2D-enabled MEC offloading scenarios, tackling interference management challenges in shared spectrum to minimize total latency. Lastly, [58] introduces a novel hybrid online-offline learning-based task offloading policy for multi-user multi-server MEC systems, showcasing notable reductions in computation delay by dynamically adjusting the offloading strategy based on MEC server queuing status and network dynamics.

3.2.2 Reduction of energy consumption

Research in this area focuses on offloading computational tasks to nearby edge servers or devices to conserve energy by reducing the workload on resource-constrained mobile devices. This involves techniques such as task consolidation, adaptive resource allocation, and energy-efficient scheduling[59-61].

In [59], an efficient approach is introduced for joint task offloading decision, local CPU frequency scheduling, power control, computation resource, and subchannel resource allocation in MEC within non-orthogonal multiple access (NOMA)-based HetNets, achieving near-optimal energy consumption savings for all users. Meanwhile, [60] proposes a Q-learning-based method for joint optimization of computation offloading and resource allocation in a dynamic multiuser MEC system, considering delay constraints and uncertain resource requirements, resulting in significant energy savings compared to baseline methods, with the DDQN-based method closely approaching exhaustive method performance. Additionally, [61] introduces a partial computation offloading strategy based on a novel hybrid metaheuristic algorithm named genetic simulated annealing-based particle swarm optimization, aiming to minimize energy consumption in a multiuser MEC system by jointly optimizing task offloading ratio, CPU speeds, allocated bandwidth of available channels, and transmission power.

3.2.3 Joint optimization of latency and energy consumption

Addressing both latency and energy consumption simultaneously involves developing efficient algorithms and strategies for task offloading that optimize both factors to enhance overall system performance. This may include: trade-off analysis, hybrid approaches, and dynamic optimization[62-64].

In [62], an iterative algorithm is presented for minimizing the completion time of tasks and energy consumption of all users in an uplink NOMA-based MEC network, considering computation latency, uploading data rate, time sharing, and edge cloud capacity constraints. Additionally, [63] proposes a non-dominated sorting genetic algorithm to find a tradeoff between energy consumption and latency in an IoT-based MEC network. Furthermore, [64] introduces a dynamic online task offloading strategy to minimize the weighted sum of energy consumption and execution delay of mobile devices in an MEC system with energy harvesting capability.

3.2.4 Enhancement of capacity

By offloading computational tasks from centralized cloud servers to edge nodes, MEC aims to enhance the overall capacity and scalability of the network, accommodating the increasing demand for real-time applications and services. This involves exploring techniques such as: load balancing, edge resource provisioning, and dynamic scaling[65,66].

In [65], a graph neural network (GNN)-based collaborative deep reinforcement learning model is proposed to generate resource provisioning and mitigate strategies against distributed denial of service attacks. GNN assists in transferring computing tasks between MEC servers to alleviate load imbalance. Furthermore, [66] introduces Lyapunov and alternating direction of multipliers-based methods to obtain a joint parallel task offloading and load balancing policy for MEC systems with multiple cooperative servers. This approach addresses energy consumption and execution delays under user battery level stability and delay constraints.

3.3 Key Technologies for Enabling MEC Implementation

3.3.1 Software-defined networking (SDN)

SDN empowers dynamic management of network resources, streamlining communication between edge devices and servers to enhance network performance in MEC applications. Several research efforts have focused on leveraging SDN in MEC systems to optimize resource allocation and reduce energy consumption and processing latency [67]. In [68], the authors introduce an SDN-based MEC system, followed by the development of a stochastic game-based resource allocation algorithm leveraging prioritized experience replays to reduce energy consumption and processing latency using multiagent reinforcement learning. Furthermore, [69] presents a solution leveraging SDN for transparent session and service continuity in dynamic multi-access edge computing scenarios.

3.3.2 Network function virtualization (NFV)

NFV revolutionizes network functions by enabling dynamic deployment and scaling of services at the edge, bolstering agility and resource optimization within MEC environments. Numerous studies have investigated the application of NFV in MEC systems to optimize resource utilization and enhance service reliability. The work in [70] explores reliable virtual network function (VNF) service provisioning to ensure mobile user reliability, offering integer linear programming and logarithmic-approximation solutions. The work in [71] considers VNF placement and traffic routing in MEC settings, aiming to minimize link load ratios and fulfill user delay requisites.

3.3.3 Information centric networking (ICN)

ICN prioritizes content retrieval based on content names, promoting efficient content delivery and caching mechanisms at the edge to support MEC applications with enhanced accessibility. Several research endeavors have explored the integration of ICN principles into MEC frameworks to optimize resource allocation and bolster system capacity[72]. The study in [73] investigates optimal resource allocation in information-centric wireless networks to maximize spectrum efficiency and system capacity.

3.3.4 Network slicing

Network slicing facilitates the creation of isolated virtual networks customize for specific MEC applications or user needs, allowing for tailored network configurations and resource allocation to improve performance. Additionally, [74] introduces a scheme merging multi-access edge computing and network slicing to bolster slicing capabilities at the 5G network edge, while [75] presents a new framework optimizing network slicing in MEC systems, aiming to maximize operator revenue by optimizing slice request admission and resource allocation in light of traffic fluctuations.

3.3.5 Edge computing platforms and frameworks

Various platforms and frameworks, such as OpenNESS, AWS IoT Greengrass, Microsoft Azure IoT Edge, and Google Cloud IoT Edge, provide tools and APIs for developing and deploying edge applications. These platforms enable developers to build and manage MEC applications efficiently.

Ⅳ. Integrating MEC into 6G NTNs

In this section, we divide the 6G NTN environment into three cases and introduce the role of MEC and possible implementation scenarios, along with related research for each case. These case studies might help us understand the potential of MEC technologies for various 6G NTN application scenarios.

4.1 Access to Both TNs and NTNs

Let us first consider the case where UEs can access both TNs and NTNs for computing task offloading as depicted in Fig. 3. Satellite communication operates with multiple LEO satellites, enabling communication with UEs, BSs, and the main server. Depending on the UE's capability, some UEs can communicate with satellites using their satellite communication modules, allowing them to directly offload tasks to satellites. For UEs without satellite modules, nearby BSs or satellite gateways can support providing satellite communication links. In this network environment, MEC can be deployed at satellites and BSs (or gateways).

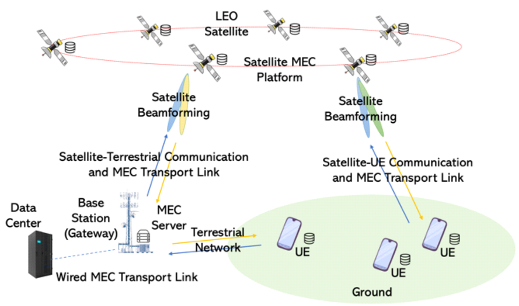

Fig. 3. MEC for accessing to both TNs and NTNs.

- **MEC at satellites**: First, we consider the task to be offloaded directly from UEs or BSs to satellites where MEC is deployed, enabling the utilization of satellite MEC for computing tasks. Additionally, the broad coverage of satellites enables the processing of tasks from a wider area of UEs[76-78]. While GEO or MEO satellites have issues with unstable connections or long latency due to their high altitude, the use of LEO satellites has mitigated these problems. However, using satellites inherently introduces a certain level of latency. In [52], a traffic distribution scheme is proposed that integrates satellite and ground networks to allocate traffic according to different needs such as ultra-reliable low latency communication (URLLC) and enhanced mobile broadband (eMBB) traffic. This scheme offloads URLLC traffic to the terrestrial backhaul to meet its stringent latency requirement, while eMBB traffic is offloaded to the satellite due to its high data rate needs and lower sensitivity to delay.
- **MEC at BSs or gateways**: Second, we consider the scenario where BSs (or gateways) are also equipped with MEC capabilities. In this case, BSs can provide edge computing and make decisions regarding the task offloading to either BSs or satellites, which is advantageous in delay-critical situations. However, this can lead to issues related to BS performance. Servicing a large number of UEs and requiring high-performance computing for MEC can result in significant power consumption and the need for high-specification equipment. Deploying high-power, high-specification BSs in complicated environments can be challenging[21,79]. In addition, BSs can offload tasks to the data center or main server, which is more suitable for heavier tasks. Since BSs are wired to the main server, communication performance is generally better when using BSs. However, relying solely on BSs can lead to traffic overload. Using satellites for traffic distribution (load balancing) or when the path to the main server is very long, communication performance through shorter hops via satellite can be better. Furthermore, deploying MEC at both satellites and ground BSs can utilize partial computing technology for faster processing. In particular, [77] introduces the problem of energy dissipation optimization in a specific case, focusing on the energy consumption of ground users and LEO systems. In such cases, the LEOs edge can coordinate with each BS server to assist in handling tasks for ground UEs. However, this increases the overall network task scheduling complexity and can lead to increased latency.

4.2 Access only to NTNs

Fig. 4 illustrates the second scenario that involves situations where communication is only possible via satellite, not terrestrial networks, applicable in extremely remote areas like open seas, deserts, or rainforests. Satellites can communicate with other satellites and eventually reach the main server. UEs with their satellite communication modules can communicate directly with satellites, and typical UEs can connect to satellites through a gateway with satellite communication capabilities. The advantage is enabling communication in special regions where no other alternatives are available, but a disadvantage is increased latency as the number of relay satellites increases[16,17,80,81].

Moreover, most researchers have studied network architectures and proposed a variety of task-processing procedures. The work in [80] introduces the architecture and application scenarios of satellite-terrestrial networks (STNs), implementing MEC for QoS improvement, and proposed satellite MEC enabling UEs

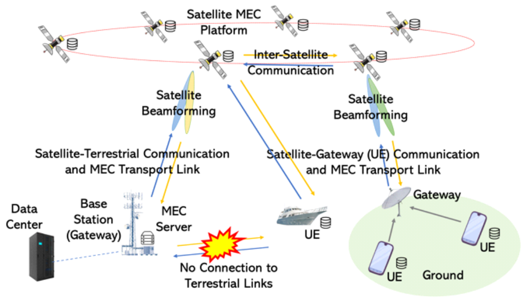

Fig. 4. MEC for accessing only to NTNs.

without a proximal MEC service can directly connect to a satellite to enjoy MEC services via satellite links. In this way, STNs also can cooperate with parallel computation satellite-terrestrial networks. In [80], multiple methods of computation offloading in SMEC have been proposed, representing various application scenarios. The work in [17] incorporates multi-layer heterogeneous edge computing clusters to enable service innovation and business agility in future networks. It addresses the challenges of meeting QoE requirements, cooperative computation offloading, multi-node task scheduling, mobility management, and fault/failure recovery. The paper highlights the need for reliable reception of large-capacity concurrent signals in the proposed architecture. It is also explored the possibility of devices with edge computing capabilities forming clusters to provide edge computing services for other devices. The work in [80] explores latency and energy cost optimization in MEC-enhanced SAT-IoT networks in remote, sparsely populated areas. It formulates the problem as a dynamic mixed-integer program, breaking it down into two sub-problems: resource allocation with fixed user association and offloading decisions, and joint user association and offloading decisions with optimal resource allocation.

4.3 UAV-Aided Access to NTNs

The third scenario involves using UAVs to support satellite link access as depicted in Fig. 5. Typically, UAVs are not commonly used for communication support due to their limited battery flight time. UAVs are deployed in challenging environments like mountains, seas, or deserts to provide support. Here, UAVs can serve as mobile BSs or relays for satellites [15,17,24,26,82,83]. In shadowed areas where there is no connection to ground BSs, UAVs can fly to provide communication services to UEs[84]. If MEC is deployed on UAVs, they can perform computing services for UEs or offload computing tasks to satellites. The work in [82] proposes a computation offloading scheme aimed at reducing energy consumption in wireless networks. Some researchers have studied the computation offloading and resource allocation issues within MEC-integrated air-ground vehicle networks

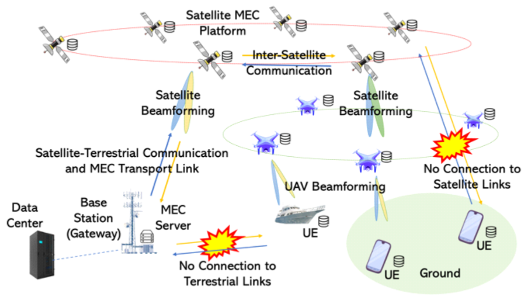

Fig. 5. MEC for UAV-aided accessing to NTNs.

[85,86]. The work in [86] addresses computation offloading and resource allocation issues within MEC-integrated aerial-terrestrial vehicular networks. To solve such complex optimization problem, a reinforcement learning-based approach was utilized.

In addition, RISs are appreciated for their ability to precisely reflect signals, enhance spectrum and energy efficiency, and regulate various waveform attributes such as amplitude, frequency, polarization, and phase through passive reflections. The discussion on the application of RIS-carried UAVs in communication systems is paralleled by the growing interest in RISs within the wireless research community [23,87]. Due to the ultra-high-frequency characteristics of the THz band, the impact of signal interference caused by obstacles is significant, so using RIS can reduce this interference. In [23], a decaying deep Q-network is proposed, which can reduce average energy consumption by combining UAV with RIS and providing joint enhancement for UAV direction, and power-sharing.

The characteristics of UAVs are key to establishing the 3D wireless communication environment expected in 6G, utilizing their mobility for optimal communication positioning and deployment without terrain or infrastructure constraints, especially in disasters or emergencies. However, limitations in battery capacity restrict flight, hence network maintenance time, and they are affected by weather and various environmental conditions. Research to overcome these limitations is underway[1,87]. For instance, a MEC-driven UAV routine inspection scheme is proposed in [87] for wind farms to reduce operating and maintenance costs and improve inspection efficiency.

V. Conclusions

This paper offers a thorough survey on the integration of 6G NTNs with MEC. First, we have reviewed characteristics and current status of 6G NTNs and the role of MEC and its key applications in different research endeavors, including latency minimization, energy efficiency, and joint optimization of energy and latency. Finally, we have explored the deployment possibilities for MEC servers and present diverse network scenarios, such as accessing both TN and NTNs, exclusive access to NTNs, and accessing NTNs via UAVs.

Future works could focus on developing adaptive resource allocation strategies for dynamic network conditions. In order to enable smooth interoperability between terrestrial and non-terrestrial MEC networks, future efforts could focus on standardization of interfaces and protocols to ensure high-quality service experience.

References

[1] FG-NET, "Network 2030: A blueprint of technology, applications and market drivers towards the year 2030 and Beyond," *ITU Geneva Switz.*, Jul. 2019. (https://www.itu.int/en/ITU-T/focusgroups/net2030/Documents/White_Paper.pdf)

[2] E. Bertin, N. Crespi, and T. Magedanz, Eds., *Shaping future 6G networks: Needs, impacts, and technologies*, Hoboken, NJ, USA: Wiley, 2022.

[3] H. Saarnisaari, et al., "A 6G white paper on connectivity for remote areas," *arXiv preprint arXiv:2004.14699*, 2020. (https://doi.org/10.48550/ARXIV.2004.14699)

[4] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Commun. Surv. Tuts.*, vol. 19, no. 4, pp. 2322-2358, 2017. (https://doi.org/10.1109/COMST.2017.2745201)

[5] Z. Ning, et al., "Mobile edge computing enabled 5G health monitoring for internet of medical things: A decentralized game theoretic approach," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 2, pp. 463-478, Feb. 2021. (https://doi.org/10.1109/JSAC.2020.3020645)

[6] M. Chen, J. Yang, J. Zhou, Y. Hao, J. Zhang, and C.-H. Youn, "5G-smart diabetes: Toward personalized diabetes diagnosis with healthcare big data clouds," *IEEE Commun. Mag.*, vol. 56, no. 4, pp. 16-23, Apr. 2018. (https://doi.org/10.1109/MCOM.2018.1700788)

[7] P. K. Bishoyi and S. Misra, "Enabling green mobile-edge computing for 5G-based healthcare applications," *IEEE Trans. Green Commun. Netw.*, vol. 5, no. 3, pp. 1623-1631, Sep. 2021. (https://doi.org/10.1109/TGCN.2021.3075903)

[8] T. Hewa, A. Braeken, M. Ylianttila, and M. Liyanage, "Multi-access edge computing and blockchain-based secure telehealth system connected with 5G and IoT," in *GLOBECOM 2020 - 2020 IEEE Global Commun. Conf.*, pp. 1-6, Taipei, Taiwan, Dec. 2020. (https://doi.org/10.1109/GLOBECOM42002.2020.9348125)

[9] X. Lin, J. Wu, A. K. Bashir, W. Yang, A. Singh, and A. A. AlZubi, "FairHealth: Long-term proportional fairness-driven 5G edge healthcare in internet of medical things," *IEEE Trans. Industrial Informatics*, vol. 18, no. 12, pp. 8905-8915, Dec. 2022. (https://doi.org/10.1109/TII.2022.3183000)

[10] M. Wu, F. R. Yu, and P. X. Liu, "Intelligence networking for autonomous driving in beyond 5G networks with multi-access edge computing," *IEEE Trans. Veh. Technol.*, vol. 71, no. 6, pp. 5853-5866, Jun. 2022. (https://doi.org/10.1109/TVT.2022.3165172)

[11] S. Pang, N. Wang, M. Wang, S. Qiao, X. Zhai, and N. N. Xiong, "A smart network resource management system for high mobility edge computing in 5G internet of vehicles," *IEEE Trans. Netw. Sci. Eng.*, vol. 8, no. 4, pp. 3179-3191, Oct. 2021. (https://doi.org/10.1109/TNSE.2021.3106955)

[12] B. Lin, X. Zhou, and J. Duan, "Dimensioning

and layout planning of 5g-based vehicular edge computing networks towards intelligent transportation," *IEEE Open J. Veh. Technol.*, vol. 1, pp. 146-155, 2020. (https://doi.org/10.1109/OJVT.2020.2988645)

[13] J. Zhang, H. Zhong, J. Cui, M. Tian, Y. Xu, and L. Liu, "Edge computing-based privacy-preserving authentication framework and protocol for 5G-enabled vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 7, pp. 7940-7954, Jul. 2020. (https://doi.org/10.1109/TVT.2020.2994144)

[14] G. Luo, et al., "Software-defined cooperative data sharing in edge computing assisted 5G-VANET," *IEEE Trans. Mob. Comput.*, vol. 20, no. 3, pp. 1212-1229, Mar. 2021. (https://doi.org/10.1109/TMC.2019.2953163)

[15] C. Liu, W. Feng, X. Tao, and N. Ge, "MEC-empowered non-terrestrial network for 6G wide-area time-sensitive internet of things," *Eng.*, vol. 8, pp. 96-107, Jan. 2022. (https://doi.org/10.1016/j.eng.2021.11.002)

[16] R. Giuliano and E. Innocenti, "Machine learning techniques for non-terrestrial networks," *Electr.*, vol. 12, no. 3, p. 652, Jan. 2023. (https://doi.org/10.3390/electronics12030652)

[17] R. Xie, Q. Tang, Q. Wang, X. Liu, F. R. Yu, and T. Huang, "Satellite-terrestrial integrated edge computing networks: Architecture, challenges, and open issues," *IEEE Netw.*, vol. 34, no. 3, pp. 224-231, May 2020. (https://doi.org/10.1109/MNET.011.1900369)

[18] M. S. Haroon, S. H. Chae, and S.-W. Jeon, "Outage analysis for multi-radio heterogeneous networks in the presence of aerial jammers," *ICT Express*, vol. 9, no. 6, pp. 1026-1031, Dec. 2023. (https://doi.org/10.1016/j.icte.2023.04.001)

[19] M. Yang, S.-W. Jeon, and D. K. Kim, "Optimal trajectory for curvature-constrained UAV mobile base stations," *IEEE Wireless Commun. Lett.*, vol. 9, no. 7, pp. 1056-1059, Jul. 2020. (https://doi.org/10.1109/LWC.2020.2980281)

[20] X. Liu, Y. Liu, and Y. Chen, "Machine learning empowered trajectory and passive beamforming design in UAV-RIS wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 7, pp. 2042-2055, Jul. 2021. (https://doi.org/10.1109/JSAC.2020.3041401)

[21] T. Naous, M. Itani, M. Awad, and S. Sharafeddine, "Reinforcement learning in the sky: A survey on enabling intelligence in NTN-based communications," *IEEE Access*, vol. 11, pp. 19941-19968, 2023. (https://doi.org/10.1109/ACCESS.2023.3236801)

[22] J. Jeong, S. H. Lim, Y. Song, and S.-W. Jeon, "Online learning for joint beam tracking and pattern optimization in massive MIMO systems," in *IEEE INFOCOM 2020 - IEEE Conf. Comput. Commun.*, pp. 764-773, Toronto, ON, Canada, Jul. 2020. (https://doi.org/10.1109/INFOCOM41043.2020.9155475)

[23] N. U. Saqib, S. Hou, S. H. Chae, and S.-W. Jeon, "RIS-aided wireless indoor communication: Sum rate maximization via RIS placement optimization," in *ICC 2023 - IEEE Int. Conf. Commun.*, pp. 511-516, Rome, Italy, May 2023. (https://doi.org/10.1109/ICC45041.2023.10278693)

[24] N. U. Saqib, S. Hou, S. H. Chae, and S.-W. Jeon, "Reconfigurable intelligent surface aided hybrid beamforming: Optimal placement and beamforming design," to appear in *IEEE Trans. Wireless Commun.*, Apr. 2024. (https://doi.org/10.1109/TWC.2024.3387449)

[25] T. Naous, M. Itani, M. Awad, and S. Sharafeddine, "Reinforcement learning in the sky: A survey on enabling intelligence in NTN-based communications," *IEEE Access*, vol. 11, pp. 19941-19968, 2023. (https://doi.org/10.1109/ACCESS.2023.3236801)

[26] N. Rahmatov and H. Baek, "RIS-carried UAV communication: Current research, challenges, and future trends," *ICT Express*, vol. 9, no. 5, pp. 961-973, Oct. 2023.

(https://doi.org/10.1016/j.icte.2023.03.004)

[27] T. Heyn, A. Hofmann, S. Raghunandan, and L. Raschkowski, "Non terrestrial networks in 6G," in *Shaping Future 6G Networks: Needs, Impacts, and Technol., IEEE*, pp. 101-116, 2022. (https://doi.org/10.1002/9781119765554.ch8)

[28] S. Razdan and S. Sharma, "Internet of medical things (IoMT): Overview, emerging technologies, and case studies," *IETE Tech. Rev.*, vol. 39, no. 4, pp. 775-788, Jul. 2022. (https://doi.org/10.1080/02564602.2021.1927863)

[29] H. Taleb, A. Nasser, G. Andrieux, N. Charara, and E. Motta Cruz, "Wireless technologies, medical applications and future challenges in WBAN: A survey," *Wireless Netw.*, vol. 27, no. 8, pp. 5271-5295, Nov. 2021. (https://doi.org/10.1007/s11276-021-02780-2)

[30] Y. Zhang, G. Chen, H. Du, X. Yuan, M. Kadoch, and M. Cheriet, "Real-time remote health monitoring system driven by 5G MEC-IoT," *Electr.*, vol. 9, no. 11, p. 1753, Oct. 2020. (https://doi.org/10.3390/electronics9111753)

[31] E. Guo and X. Cui, "Simulation of optical sensor network based on edge computing in athlete physical fitness monitoring system," *Opt. Quantum Electr.*, vol. 56, no. 4, p. 637, Feb. 2024. (https://doi.org/10.1007/s11082-024-06282-1)

[32] D. A. Meshram and D. D. Patil, "5G enabled tactile internet for tele-robotic surgery," *Procedia Comput. Sci.*, vol. 171, pp. 2618-2625, 2020. (https://doi.org/10.1016/j.procs.2020.04.284)

[33] P. Consul, I. Budhiraja, R. Arora, S. Garg, B. J. Choi, and M. Shamim Hossain, "Federated reinforcement learning based task offloading approach for MEC-assisted WBAN-enabled IoMT," *Alex. Eng. J.*, vol. 86, pp. 56-66, Jan. 2024. (https://doi.org/10.1016/j.aej.2023.11.041)

[34] J. Zhou, H. Xia, H. Zuo, and C. Tellambura, "Time minimization for health monitoring systems in internet of medical things via rate splitting," *IEEE Internet Things J.*, vol. 11, no. 4, pp. 7186-7197, Feb. 2024. (https://doi.org/10.1109/JIOT.2023.3315372)

[35] Y. Li, Y. Wang, S. Chen, X. Huang, and T. Huang, "Resource allocation and data offloading strategy for edge-computing-assisted intelligent telemedicine system," *Sensors*, vol. 23, no. 10, p. 4943, May 2023. (https://doi.org/10.3390/s23104943)

[36] Z. Askari, J. Abouei, M. Jaseemuddin, and A. Anpalagan, "Energy-efficient and real-time NOMA scheduling in IoMT-based three-tier WBANs," *IEEE Internet Things J.*, vol. 8, no. 18, pp. 13975-13990, Sep. 2021. (https://doi.org/10.1109/JIOT.2021.3069659)

[37] X. Yuan, et al., "A DQN-based frame aggregation and task offloading approach for edge-enabled IoMT," *IEEE Trans. Netw. Sci. Eng.*, vol. 10, no. 3, pp. 1339-1351, May 2023. (https://doi.org/10.1109/TNSE.2022.3218313)

[38] A. Saxena and S. Mittal, "Internet of medical things (IoMT) security and privacy: A survey of recent advances and enabling technologies," in *Proc. 2022 Fourteenth Int. Conf. Contemporary Comput.*, pp. 550-559, Noida India, Aug. 2022. (https://doi.org/10.1145/3549206.3549301)

[39] T. Cerquitelli, et al., "A fog computing approach for predictive maintenance," in *Advanced Inf. Syst. Eng. Wkshps.: CAiSE 2019 Int. Wkshps.*, pp. 139-147, Rome, Italy, 2019. (https://doi.org/10.1007/978-3-030-20948-3_13)

[40] H. Ha and J. Jeong, "CNN-based defect inspection for injection molding using edge computing and industrial IoT systems," *Appl. Sci.*, vol. 11, no. 14, p. 6378, Jul. 2021. (https://doi.org/10.3390/app11146378)

[41] Z. Zhao, P. Lin, L. Shen, M. Zhang, and G. Q. Huang, "IoT edge computing-enabled collaborative tracking system for manufacturing resources in industrial park," *Adv. Eng. Inf.*, vol. 43, p. 101044, Jan. 2020. (https://doi.org/10.1016/j.aei.2020.101044)

[42] C. Xu and G. Zhu, "Intelligent manufacturing

lie group machine learning: Real-time and efficient inspection system based on fog computing," *J. Intell. Manuf.*, vol. 32, no. 1, pp. 237-249, Jan. 2021. (https://doi.org/10.1007/s10845-020-01570-5)

[43] C. Jiang, J. Wan, and H. Abbas, "An edge computing node deployment method based on improved *k*-means clustering algorithm for smart manufacturing," *IEEE Syst. J.*, vol. 15, no. 2, pp. 2230-2240, Jun. 2021. (https://doi.org/10.1109/JSYST.2020.2986649)

[44] J. Wang, D. Li, and Y. Hu, "Fog nodes deployment based on space-time characteristics in smart factory," *IEEE Trans. Ind. Inf.*, vol. 17, no. 5, pp. 3534-3543, May 2021. (https://doi.org/10.1109/TII.2020.2999310)

[45] P. K. Malik, et al., "Industrial internet of things and its applications in industry 4.0: State of the art," *Comput. Commun.*, vol. 166, pp. 125-139, Jan. 2021. (https://doi.org/10.1016/j.comcom.2020.11.016)

[46] X. Dai, et al., "Task co-offloading for D2D-assisted mobile edge computing in industrial internet of things," *IEEE Trans. Ind. Inf.*, vol. 19, no. 1, pp. 480-490, Jan. 2023. (https://doi.org/10.1109/TII.2022.3158974)

[47] Z. Tong, J. Cai, J. Mei, K. Li, and K. Li, "Computation offloading for energy efficiency maximization of sustainable energy supply network in IIoT," *IEEE Trans. Sustain. Comput.*, vol. 9, no. 2, pp. 128-140, Mar. 2024. (https://doi.org/10.1109/TSUSC.2023.3313770)

[48] C. Tang, C. Zhu, N. Zhang, M. Guizani, and J. J. P. C. Rodrigues, "SDN-assisted mobile edge computing for collaborative computation offloading in industrial internet of things," *IEEE Internet Things J.*, vol. 9, no. 23, pp. 24253-24263, Dec. 2022. (https://doi.org/10.1109/JIOT.2022.3190281)

[49] L. Zhou, H. Guo, and G. Deng, "A fog computing based approach to DDoS mitigation in IIoT systems," *Comput. Secur.*, vol. 85, pp. 51-62, Aug. 2019. (https://doi.org/10.1016/j.cose.2019.04.017)

[50] Y. Yu, L. Xue, Y. Li, X. Du, M. Guizani, and B. Yang, "Assured data deletion with fine-grained access control for fog-based industrial applications," *IEEE Trans. Ind. Inf.*, vol. 14, no. 10, pp. 4538-4547, Oct. 2018. (https://doi.org/10.1109/TII.2018.2841047)

[51] Y. Cheng, "Edge caching and computing in 5G for mobile augmented reality and haptic internet," *Comput. Commun.*, vol. 158, pp. 24-31, May 2020. (https://doi.org/10.1016/j.comcom.2020.04.054)

[52] P. Ren, X. Qiao, Y. Huang, L. Liu, S. Dustdar, and J. Chen, "Edge-assisted distributed DNN collaborative computing approach for mobile web augmented reality in 5G networks," *IEEE Netw.*, vol. 34, no. 2, pp. 254-261, Mar. 2020. (https://doi.org/10.1109/MNET.011.1900305)

[53] Z. Li, H. Zhang, X. Li, H. Ji, and V. C. M. Leung, "Distributed task scheduling for MEC-assisted virtual reality: A fully-cooperative multi-agent perspective," *IEEE Trans. Veh. Technol.*, pp. 1-15, 2024. (https://doi.org/10.1109/TVT.2024.3365476)

[54] P. Ren, et al., "Edge AR X5: An edge-assisted multi-user collaborative framework for mobile web augmented reality in 5G and beyond," *IEEE Trans. Cloud Comput.*, vol. 10, no. 4, pp. 2521-2537, Oct. 2022. (https://doi.org/10.1109/TCC.2020.3046128)

[55] J. Ren, G. Yu, Y. He, and G. Y. Li, "Collaborative cloud and edge computing for latency minimization," *IEEE Trans. Veh. Technol.*, vol. 68, no. 5, pp. 5031-5044, May 2019. (https://doi.org/10.1109/TVT.2019.2904244)

[56] T. Bai, C. Pan, Y. Deng, M. Elkashlan, A. Nallanathan, and L. Hanzo, "Latency minimization for intelligent reflecting surface aided mobile edge computing," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 11, pp. 2666-2682, Nov. 2020. (https://doi.org/10.1109/JSAC.2020.3007035)

[57] U. Saleem, Y. Liu, S. Jangsher, X. Tao, and Y. Li, "Latency minimization for D2D-

enabled partial computation offloading in mobile edge computing," *IEEE Trans. Veh. Technol.*, vol. 69, no. 4, pp. 4472-4486, Apr. 2020. (https://doi.org/10.1109/TVT.2020.2978027)

[58] M. Sohaib, S.-W. Jeon, and W. Yu, "Hybrid online-offline learning for task offloading in mobile edge computing systems," to appear in *IEEE Trans. Wireless Commun.* vol. 23, no. 7, pp. 6873-6888, Dec. 2023. (https://doi.org/10.1109/TWC.2023.3335362)

[59] C. Xu, G. Zheng, and X. Zhao, "Energy-minimization task offloading and resource allocation for mobile edge computing in NOMA heterogeneous networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 12, pp. 16001-16016, Dec. 2020. (https://doi.org/10.1109/TVT.2020.3040645)

[60] H. Zhou, K. Jiang, X. Liu, X. Li, and V. C. M. Leung, "Deep reinforcement learning for energy-efficient computation offloading in mobile-edge computing," *IEEE Internet Things J.*, vol. 9, no. 2, pp. 1517-1530, Jan. 2022. (https://doi.org/10.1109/JIOT.2021.3091142)

[61] J. Bi, H. Yuan, S. Duanmu, M. Zhou, and A. Abusorrah, "Energy-optimized partial computation offloading in mobile-edge computing with genetic simulated-annealing-based particle swarm optimization," *IEEE Internet Things J.*, vol. 8, no. 5, pp. 3774-3785, Mar. 2021. (https://doi.org/10.1109/JIOT.2020.3024223)

[62] Z. Yang, C. Pan, J. Hou, and M. Shikh-Bahaei, "Efficient resource allocation for mobile-edge computing networks with NOMA: Completion time and energy minimization," *IEEE Trans. Commun.*, vol. 67, no. 11, pp. 7771-7784, Nov. 2019. (https://doi.org/10.1109/TCOMM.2019.2935717)

[63] L. Cui, et al., "Joint optimization of energy consumption and latency in mobile edge computing for internet of things," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4791-4803, Jun. 2019. (https://doi.org/10.1109/JIOT.2018.2869226)

[64] G. Zhang, W. Zhang, Y. Cao, D. Li, and L. Wang, "Energy-delay tradeoff for dynamic offloading in mobile-edge computing system with energy harvesting devices," *IEEE Trans. Ind. Inf.*, vol. 14, no. 10, pp. 4642-4655, Oct. 2018. (https://doi.org/10.1109/TII.2018.2843365)

[65] Y. Deng, et al., "Resource provisioning for mitigating edge DDoS attacks in MEC-enabled SDVN," *IEEE Internet Things J.*, vol. 9, no. 23, pp. 24264-24280, Dec. 2022. (https://doi.org/10.1109/JIOT.2022.3189975)

[66] W. Zhang, G. Zhang, and S. Mao, "Joint parallel offloading and load balancing for cooperative-MEC systems with delay constraints," *IEEE Trans. Veh. Technol.*, vol. 71, no. 4, pp. 4249-4263, Apr. 2022. (https://doi.org/10.1109/TVT.2022.3143425)

[67] A. C. Baktir, A. Ozgovde, and C. Ersoy, "How can edge computing benefit from software-defined networking: A survey, use cases, and future directions," *IEEE Commun. Surv. Tuts..*, vol. 19, no. 4, pp. 2359-2391, 2017. (https://doi.org/10.1109/COMST.2017.2717482)

[68] G. Wu, H. Wang, H. Zhang, Y. Zhao, S. Yu, and S. Shen, "Computation offloading method using stochastic games for software-defined-network-based multiagent mobile edge computing," *IEEE Internet Things J.*, vol. 10, no. 20, pp. 17620-17634, Oct. 2023. (https://doi.org/10.1109/JIOT.2023.3277541)

[69] P. Fondo-Ferreiro, F. Gil-Castineira, F. J. Gonzalez-Castano, and D. Candal-Ventureira, "A software-defined networking solution for transparent session and service continuity in dynamic multi-access edge computing," *IEEE Trans. Netw. Serv. Manag.*, vol. 18, no. 2, pp. 1401-1414, Jun. 2021. (https://doi.org/10.1109/TNSM.2020.3033071)

[70] M. Huang, W. Liang, X. Shen, Y. Ma, and H. Kan, "Reliability-aware virtualized network function services provisioning in mobile edge computing," *IEEE Trans. Mob. Comput.*, vol. 19, no. 11, pp. 2699-2713, Nov. 2020.

(https://doi.org/10.1109/TMC.2019.2927214)

[71] S. Yang, F. Li, S. Trajanovski, X. Chen, Y. Wang, and X. Fu, "Delay-aware virtual network function placement and routing in edge clouds," *IEEE Trans. Mob. Comput.*, vol. 20, no. 2, pp. 445-459, Feb. 2021. (https://doi.org/10.1109/TMC.2019.2942306)

[72] R. Ullah, S. H. Ahmed, and B.-S. Kim, "Information-centric networking with edge computing for IoT: Research challenges and future directions," *IEEE Access*, vol. 6, pp. 73465-73488, 2018. (https://doi.org/10.1109/ACCESS.2018.2884536)

[73] D. Wang, H. Qin, B. Song, X. Du, and M. Guizani, "Resource allocation in information-centric wireless networking with D2D-enabled MEC: A deep reinforcement learning approach," *IEEE Access*, vol. 7, pp. 114935-114944, 2019. (https://doi.org/10.1109/ACCESS.2019.2935545)

[74] A. Ksentini and P. A. Frangoudis, "Toward slicing-enabled multi-access edge computing in 5G," *IEEE Netw.*, vol. 34, no. 2, pp. 99-105, Mar. 2020. (https://doi.org/10.1109/MNET.001.1900261)

[75] J. Feng, Q. Pei, F. R. Yu, X. Chu, J. Du, and L. Zhu, "Dynamic network slicing and resource allocation in mobile edge computing systems," *IEEE Trans. Veh. Technol.*, vol. 69, no. 7, pp. 7863-7878, Jul. 2020. (https://doi.org/10.1109/TVT.2020.2992607)

[76] W. Abderrahim, O. Amin, M.-S. Alouini, and B. Shihada, "Latency-aware offloading in integrated satellite terrestrial networks," *IEEE Open J. Commun. Soc.*, vol. 1, pp. 490-500, 2020. (https://doi.org/10.1109/OJCOMS.2020.2988787)

[77] X. Cao, et al., "Edge-assisted multi-layer offloading optimization of LEO satellite-terrestrial integrated networks," *IEEE J. Sel. Areas Commun.*, vol. 41, no. 2, pp. 381-398, Feb. 2023. (https://doi.org/10.1109/JSAC.2022.3227032)

[78] Y. He, Y. Gan, H. Cui, and M. Guizani, "Fairness-based 3-D multi-UAV trajectory optimization in multi-UAV-assisted MEC system," *IEEE Internet Things J.*, vol. 10, no. 13, pp. 11383-11395, Jul. 2023. (https://doi.org/10.1109/JIOT.2023.3241087)

[79] G. Cui, X. Li, L. Xu, and W. Wang, "Latency and energy optimization for MEC enhanced SAT-IoT networks," *IEEE Access*, vol. 8, pp. 55915-55926, 2020. (https://doi.org/10.1109/ACCESS.2020.2982356)

[80] Z. Zhang, W. Zhang, and F.-H. Tseng, "Satellite mobile edge computing: Improving QoS of high-speed satellite-terrestrial networks using edge computing techniques," *IEEE Netw.*, vol. 33, no. 1, pp. 70-76, Jan. 2019. (https://doi.org/10.1109/MNET.2018.1800172)

[81] X. Song, M. Cheng, L. Lei, and Y. Yang, "Multitask and multiobjective joint resource optimization for UAV-assisted air-ground integrated networks under emergency scenarios," *IEEE Internet Things J.*, vol. 10, no. 23, pp. 20342-20357, Dec. 2023. (https://doi.org/10.1109/JIOT.2023.3284425)

[82] 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," *arXiv preprint arXiv: 2401.01140*, 2024. (https://doi.org/10.48550/arXiv.2401.01140)

[83] Y.-H. Chao, C.-H. Chung, C.-H. Hsu, Y. Chiang, H.-Y. Wei, and C.-T. Chou, "Satellite-UAV-MEC collaborative architecture for task offloading in vehicular networks," in *2020 IEEE GC Wkshps.*, pp. 1-6, Taipei, Taiwan, Dec. 2020. (https://doi.org/10.1109/GCWkshps50303.2020.9367543)

[84] M. Kang and S.-W. Jeon, "Energy-efficient data aggregation and collection for multi-UAV-enabled IoT networks," *IEEE Wireless Commun. Lett.*, p. 1, 2024. (https://doi.org/10.1109/LWC.2024.3355934)

[85] N. Waqar, S. A. Hassan, A. Mahmood, K. Dev, D.-T. Do, and M. Gidlund,

"Computation offloading and resource allocation in MEC-enabled integrated aerial-terrestrial vehicular networks: A reinforcement learning approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 11, pp. 21478-21491, Nov. 2022.
(https://doi.org/10.1109/TITS.2022.3179987)

[86] Y. Lyu, Z. Liu, R. Fan, C. Zhan, H. Hu, and J. An, "Optimal computation offloading in collaborative LEO-IoT enabled MEC: A multiagent deep reinforcement learning approach," *IEEE Trans. Green Commun. Netw.*, vol. 7, no. 2, pp. 996-1011, Jun. 2023.
(https://doi.org/10.1109/TGCN.2022.3186792)

[87] P. Cao, Y. Liu, C. Yang, S. Xie, and K. Xie, "MEC-driven UAV-enabled routine inspection scheme in wind farm under wind influence," *IEEE Access*, vol. 7, pp. 179252-179265, 2019.
(https://doi.org/10.1109/ACCESS.2019.2958680)

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