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Satellite-MEC Integration for 6G Internet of Things: Minimal Structures, Advances, and Prospects

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ABSTRACT The sixth-generation (6G) network is envisioned to shift its focus from the service requirements of human beings to those of Internet-of-Things (IoT) devices. Satellite communications are indispensable in 6G to support IoT devices operating in rural or disaster areas. However, satellite networks face the inherent challenges of low data rate and large latency, which may not support computation-intensive and delay-sensitive IoT applications. Mobile Edge Computing (MEC) is a burgeoning paradigm by extending cloud computing capabilities to the network edge. Using MEC technologies, the resource-limited IoT devices can access abundant computation resources with low latency, which enables the highly demanding applications while meeting strict delay requirements. Therefore, an integration of satellite communications and MEC technologies is necessary to better enable 6G IoT. In this survey, we provide a holistic overview of satellite-MEC integration. We first categorize the related studies based on three minimal structures and summarize current advances. For each minimal structure, we discuss the lessons learned and possible future directions. We also summarize studies considering the combination of minimal structures. Finally, we outline potential research issues to envision a more intelligent, more secure, and greener integrated satellite-MEC network.

INDEX TERMS Computation offloading, Internet of Things (IoT), mobile edge computing (MEC), satellite communications, satellite-MEC integration.

I. INTRODUCTION

The past few years have witnessed the proliferation of intelligent Internet-of-Things (IoT) devices, such as wireless sensors, industrial robots and intelligent vehicles. With connection to the Internet, these IoT devices can enable a myriad of emerging applications (e.g., autonomous driving). The number of connected IoT devices will reach 30 billion by the end of 2025 [1] [2]. As a consequence, future sixth-generation (6G) networks will focus mainly on serving these intelligent IoT devices instead of human beings. Providing IoT devices with satisfactory services raises challenges for the design of wireless systems. One major challenge is

that a considerable part of the IoT devices are deployed in remote areas, such as oceans, deserts and forests, for environmental monitoring and resource exploitation [3]. The harsh geographical conditions in these areas make it difficult or expensive to construct traditional terrestrial infrastructures in fifth-generation (5G) networks [4] [5]. In addition, some IoT devices are required in disastrous areas, where terrestrial infrastructures may suffer from serious damage [6]. To address this, a non-terrestrial network via satellites and unmanned aerial vehicles (UAVs) may be used to complement the terrestrial network and fill the coverage gap [7] [8].

Satellite communications are considered a promising solution to providing ubiquitous broadband Internet access at low cost [9] [10]. Geostationary earth orbit (GEO) satellite networks, which are traditionally used for satellite communications, have experienced rapid developments in terms of providing high speed services to global users [11]. Moreover, low earth orbit (LEO) constellation networks have attracted great attention due to their lower propagation latency and higher transmission rate [12]. Several commercial projects of LEO satellite communication, such as OneWeb, Telesat, and Starlink, have been launched. Despite the many advantages, satellite networks also face their inherent challenges. Compared with terrestrial networks, satellite networks typically have lower data rate and larger latency. In computation-intensive applications, IoT devices may need to offload their data for cloud computing, due to their limited computing resources. Offloading through satellites can lead to a long delay, which is unacceptable for IoT devices that require delay-sensitive services.

To address these challenges, one promising direction is to enable edge intelligence to replace traditional cloud computing [13]. The basic idea is to extend cloud computing capabilities to the network edge to enable artificial intelligence (AI) applications, allowing the IoT devices to be endowed with low-latency data processing and decision-making capabilities. Mobile edge computing (MEC) technologies play an important role in the edge intelligence paradigm. In current 5G networks, MEC technologies have been used to enhanced the service quality for human beings. We envision that integrating satellite networks and MEC can better support IoT applications in remote or disastrous areas as well [14].

Preliminary attempts have been made to integrate satellite communications and MEC technologies. For instance, Hewlett Packard Enterprise (HPE) partnered with National Aeronautics and Space Administration (NASA) to first launch computers to the International Space Station, namely the HPE SpaceBorne Computer, which managed to operate during its full time aboard. In addition, the cloud service providers (*e.g.*, Amazon, Microsoft and Google) have explored cloud-based ground stations which directly connect satellites with ground data centers.

However, the design of integrated satellite-MEC networks also face several challenges. First, the temporal and spatial distributions of the IoT devices' service requirements are sparse and heterogeneous, and they could vary significantly over time in terms of service number, service type, *etc.* Besides, the communication and computing resources of the integrated satellite-MEC network are limited. On the one hand, satellite communications are inherently limited in data rate and latency, and the limited orbit resources restrict the number of operating satellites. On the other hand, the MEC servers deployed on satellites or UAVs are restricted in terms of size, weight and energy. Moreover, it is challenging to configure the appropriate network resources to match the

service requirements to achieve higher resource efficiency. There exist hierarchical network resources in the network such as the communication links of different features and multiple layers of edge servers. Meanwhile, the resources could change dynamically due to the mobility of UAVs and LEO satellites, making this problem complicated. Last but not least, the harsh space environment renders deploying MEC servers on satellites difficult. Space radiation is one of the most important factors. It not only causes cumulative effects that could influence the operational parameters of on-board devices, but also triggers single-event effects that lead to operational errors or even device damages [15]. In addition to radiation, the low temperature and vacuum in space could also cause damage to electronic devices [16]. To overcome these difficulties, certain mitigation measures need to be taken, which could incur additional costs and bring new challenges to integrated satellite-MEC networks' system design.

With the above-mentioned challenges, the design of an integrated satellite-MEC network is still an open issue, and a number of studies have discussed this problem. There are a few relevant survey papers on this subject. For instance, [17] summarized the advances on satellite communication networks and reviewed studies that consider enabling edge computing on satellites. In addition, [18] reviewed the existing studies that consider a three-layer network, where the air- and space-layer infrastructures are equipped with MEC servers to provide services for users on the ground layer. Although these surveys have made great contributions, they focus on a special scenario of satellite-MEC integration. The absence of a comprehensive review on integrated satellite-MEC networks underlines the motivation for this article.

Referring to [19], a complex integrated satellite-MEC network could be considered as an orchestration of three minimal network structures, which are regarded as the basic elements of the integrated satellite-MEC network. These minimal structures have unique network properties, and therefore differ in the enabled applications as well as the design challenges. After the literature review, we believe that all existing works are either based on one of the minimal structures or a combination of multiple minimal structures. Therefore, the outline of this survey is presented as follows.

- First, we summarize the studies that are based on the computing-in-forward-link (CIF) structure, where MEC servers are deployed on aerial platforms (APs) connected to the satellite, as shown in Fig. 1(a). By deploying MEC servers in proximity to IoT devices, the CIF structure is suitable for local-area applications with ultra-low latency requirements. However, the central processing unit (CPU) capability of an on-board MEC server is restricted since APs are limited in size and energy, which should be considered in the system design.
- Then we discuss the related studies considering the computing-on-orbit (COO) structure, where MEC

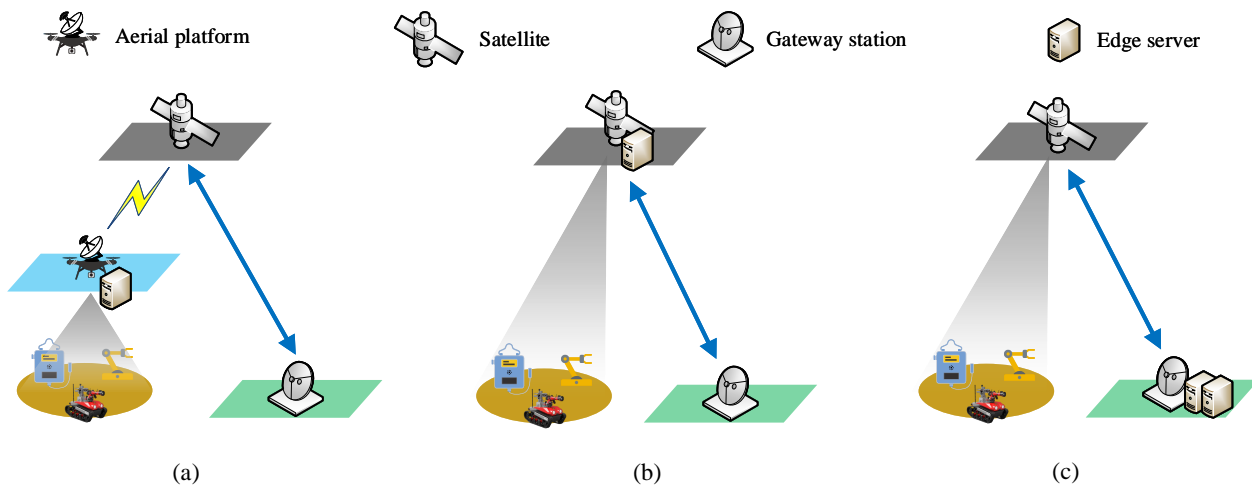


FIGURE 1. Illustration of minimal structures of integrated satellite-MEC networks (a) CIF structure (b) COO structure (c) CAF structure [19].

servers are deployed directly on satellites, as shown in Fig. 1(b). Since satellites provide much larger coverage than APs, the COO structure can well support wide-area applications with low latency requirements. However, the minimal structure system design faces multiple challenges due to the harsh space environment and the limitations of satellites in terms of size, weight and energy.

- The third category of studies are based on the computing-after-feeder-link (CAF) structure, where MEC servers are deployed at the gateway station, as shown in Fig. 1(c). In this minimal structure configuration, the MEC servers are endowed with enhanced CPU capabilities. However, this also results in increased latency for IoT devices accessing these servers. Therefore, the CAF structure is suitable for wide-area computation-intensive but delay-tolerant applications.
- Finally, we summarize the studies that consider the combination of different minimal structures.

The rest of this paper is organized as follows. In Sections II, III, IV, we summarize the related studies that are based on the three minimal structures respectively. We further discuss the learned lessons and possible future directions for each minimal structure. In Section V, we review the studies that investigate the combination of the minimal structures. Finally, Section VI outlines open issues, and Section VII draws the conclusion.

II. COMPUTING-IN-FORWARD-LINK STRUCTURE

The first minimal structure is the CIF structure. As shown in Fig. 1(a), this minimal integrating structure consists of an AP equipped with an MEC server, a satellite, a gateway and multiple IoT devices. The AP can be a UAV or a high-altitude platform (HAP). This minimal structure can be extended by considering multiple APs in the network, as shown in Fig. 2. Existing studies based on the CIF structure

primarily focus on two key areas: computation offloading and content delivery.

A. COMPUTATION OFFLOADING

Computation task offloading is a basic service provided by integrated satellite-MEC networks. For the CIF structure, an important problem is to properly allocate different users' computation tasks to MEC servers. To solve the problem, it is necessary to comprehensively consider the characteristics of computation tasks (e.g., delay requirement, input data size), as well as the heterogeneous communication and computation resources in the network.

In [20], the CIF network consisted of a satellite and a multi-antenna access point with MEC capabilities. The access point worked in full-duplex mode, and thus the computation results could be transmitted back to users in real time. To improve the offloading data rate, the authors investigated users' task offloading decision and resource allocation jointly. The authors of [21] considered utilizing satellite and multiple UAVs in the network, where the UAVs were equipped with MEC servers to provide computation services. In this paper, the task offloading decision was jointly designed with the allocation of user power, bandwidth and computing resources, and the aim was to minimize the total energy cost in the system. The authors proposed an algorithm based on double deep Q-learning as a solution. In [22], multiple UAVs and multiple ground base stations, all equipped with MEC servers, were used to provide edge computing services. An LEO satellite was connected to both the UAVs and the base stations for backhaul transmission. A joint UAV placement and task offloading decision problem was considered in the network to maximize the overall profit of the MEC service provider, which was determined by the number of completed computation tasks and the energy consumption of the MEC servers. The authors provided a two-stage algorithm to solve this problem.

TABLE 1. Summary of Advances on the CIF structure

Theme	Ref.	Network architecture	Design objective	Proposed solution
Computation offloading	[20]	A satellite and a ground base station	Task offloading rate	Design users' task offloading decision and resource allocation, and provide a solution by decomposing the problem into two sub-problems.
	[21]	A satellite and multiple UAVs	Energy	Jointly optimize the users' task offloading decision and resource allocation and propose a scheme based on double deep Q-learning.
	[22]	A satellite, multiple UAVs and multiple ground base stations	Profit of MEC service provider	Jointly optimize the users' task offloading decision and UAV placement and propose a two-stage algorithm.
Content delivery	[23]	MEC-enabled radio access network (RAN) with satellite backhaul	/	Investigate two use cases for popular and personalized content delivery.
	[24]	MEC-enabled RAN with satellite and terrestrial backhaul	/	Propose a content delivery strategy to achieve optimal traffic distribution among satellite and terrestrial backhaul links.
	[25]	MEC-enabled RAN with satellite backhaul	/	Propose a SR-based adaptive video streaming scheme.

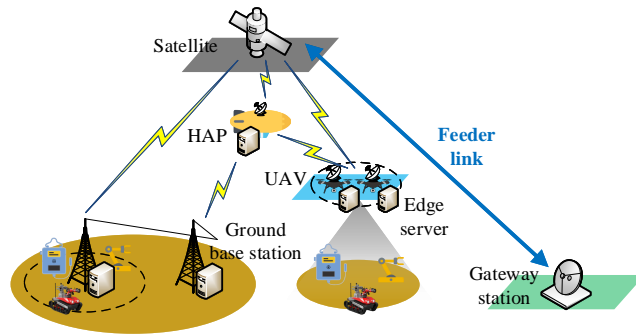


FIGURE 2. Illustration of one possible extension of the CIF structure.

B. CONTENT DELIVERY

In addition to computation offloading, another important service considered in the CIF structure is the delivery of bandwidth-demanding application data, such as high-resolution video streaming. Specifically, the broadcasting/multicasting capability of satellite communication enables content delivery to multiple network locations, where the data can be stored in MEC servers in proximity to users. However, the system design still faces multiple challenges due to the limited network resources and long latency, and thus multiple studies have been conducted toward efficient content delivery.

The authors of [23] proposed a network architecture where a CIF satellite-MEC network was utilized to support mobile video delivery. In this network, the authors investigated two use cases to enhance the users' Quality of Experience (QoE). One use case used utilizing satellite communications to pre-populate video content to MEC servers at different locations based on the predictive content popularity. The other use case pre-fetched video content segments to the MEC servers, in order to overcome the long propagation latency of satellite

links. In [24], a similar CIF structure was considered, except that both terrestrial and satellite backhaul links were included. The MEC server selected a backhaul link for each enhancement layer of the video, based on the playout buffer size. The authors proposed a content delivery strategy to achieve optimal traffic distribution among the backhaul links. The authors of [25] proposed a super-resolution-based (SR-based) adaptive video streaming scheme in a CIF satellite-MEC network. Specifically, this SR-based method transmitted low-resolution images through the satellite links to overcome the limited transmission rate. The MEC server provided the computation resources necessary to run a deep neural network to reconstruct low-resolution images to high-resolution images. Table 1 gives a summary of all these works.

C. LESSONS LEARNED AND FUTURE DIRECTIONS

Existing works based on the CIF structure mainly focus on two aspects. The first is the task offloading decision problem in computation offloading, and the second is content delivery. Potential new research avenues are listed as follows.

Initially, new design objectives may be contemplated to enhance system performance. For instance, while prior studies on task offloading decisions have considered energy cost or other metrics as design objectives, the CIF structure mainly emphasized delay-sensitive services. Future research could integrate task latency as a key design objective.

Besides, there are also new topics that warrant discussion. For instance, a critical issue is determining the on-board MEC capability for HAPs or UAVs. In addressing this issue, the number of service requirements and the energy consumption are important factors to be considered. Since the flight duration of an HAP can extend to months, configuring the MEC capability on HAPs is a large-time scale problem. In

this case, the design of the MEC capability may be based on the average service requirement number, which can be estimated by analyzing historical data. For the UAV case, however, the duration of one flight is only a few hours. In this case, the MEC capability configured for UAVs can be further optimized based on more specific information. For instance, the large-scale channel state information (CSI) during the UAV's flight can be conveniently acquired from a pre-established database, referred to as a radio map [26]. This external information can assist the on-board MEC capability configuration. Consequently, a new framework for medium-timescale network adjustment based on external information needs to be introduced—an area ripe for further exploration.

Additionally, the task pre-processing problem can be considered in this basic structure. Specifically, for computation tasks that have a huge input data size, the MEC servers can pre-process the task to compress the data size before offloading it to the cloud. This aspect of network management also warrants additional discussion.

III. COMPUTING-ON-ORBIT STRUCTURE

The second minimal structure is the COO structure. This minimal integrating structure is composed of a satellite equipped with an MEC server, a gateway and multiple IoT devices, as shown in Fig. 1(b). There are several variants of this minimal structure. For instance, the space segment can be a constellation of LEO satellites. In addition, a GEO satellite and an LEO constellation can coordinately provide edge computing services, as shown in Fig. 3. The existing studies based on the COO structure mainly focus on three topics, namely MEC server placement, service placement and computation offloading.

A. MEC SERVER PLACEMENT

Since there can be multiple satellites on different orbits in space, the first problem of the COO structure is to determine on which satellites the MEC servers are placed. On the one hand, because of the harsh space environments such as the severe radiation, placing MEC servers on satellites requires hardening measures for the servers, which could in-

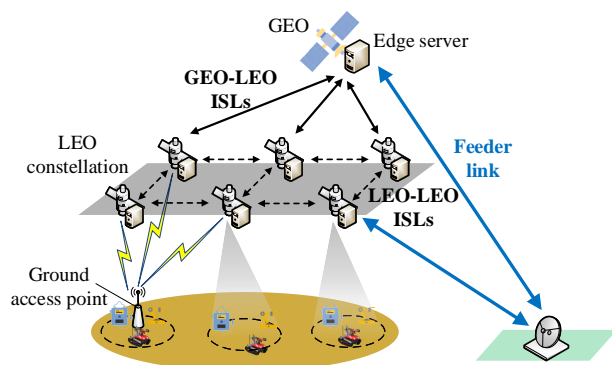


FIGURE 3. Illustration of one possible extension of the COO structure.

cur additional costs. On the other hand, the satellites without MEC server equipment may need better inter-satellite links (ISLs) to offload their tasks. This leads to a tradeoff that requires careful consideration. Moreover, the temporal and spatial distributions of the service requirements should also be considered, which makes the problem more complicated.

In this context, both [27] and [28] explored the problem of server placement in a COO network with an LEO constellation in space. By modeling the LEO constellation as a two-dimensional torus network, the authors of [27] aimed to place a minimum number of servers so that every satellite can access a server within a threshold distance. To achieve optimal server placement, an algorithm based on the d -hops placement method was proposed. On the other hand, the authors of [28] focused on computation latency and considered two server placement problems. The first problem aimed to minimize the task response delay at a given snapshot, while the second aimed to minimize the average response delay for an entire time period. A heuristic scheme based on the genetic algorithm was proposed to solve both problems. The proposed scheme yielded a performance gain over traditional schemes, as it took into account the temporal and spatial characteristics of LEO satellite networks.

B. SERVICE PLACEMENT

The execution of a computation task requires not only computation resources but also a set of codes and related libraries/databases. The MEC server can store the code and databases of certain services, which is referred to as service placement. Therefore, the next problem of the COO structure is the service placement decision of the satellite-based MEC servers. We note that the service placement problem is different from the above-mentioned server placement problem, where the former decides how to deploy the software and database of different applications on satellite-based MEC servers, while the latter decides whether or not the satellites should be equipped with MEC servers. For the service placement problem, it is of great importance to consider how different types of service requirements are distributed spatially.

In [29], the authors considered a COO system, where a constellation of satellites each equipped with an MEC server provided computing services. The service placement problem was investigated to maximize the robustness aware service coverage of the system. Specifically, the problem aimed to increase the user request number that can access the service, as well as the user request number that can access more than one service copy deployed on different satellite-based servers. The authors proposed an online service placement algorithm based on Lyapunov optimization and Gibbs sampling to give a near-optimal solution. The authors of [30] further extended the system in [29] considering ISLs among LEO satellites. The joint service placement and service request scheduling problem was investigated, which aimed to reduce unsatisfactory service requests while minimizing

ISL transmission cost. The authors modeled it as a mixed-integer linear programming problem and provided a solution, which showed better performance than greedy methods.

C. COMPUTATION OFFLOADING

For the COO structure, in addition to MEC server placement and service placement, another important problem is to properly offload users' computation tasks to MEC servers. To solve this problem, it is necessary to comprehensively consider the characteristics of computation tasks (e.g., delay requirement, input data size), as well as the heterogeneous communication and computation resources in the network.

In [31], the authors considered utilizing a single LEO satellite with MEC equipment for computation offloading. Specifically, ground users process their task data locally or offload the data to the MEC-enabled satellite, where the to-be-processed data wait in task queues. The joint offloading decision and communication and computing resource allocation problem was investigated to minimize the long-term power cost. To solve the problem, the Lyapunov optimization was employed for problem decomposition and an online algorithm combining deep reinforcement learning and conventional optimization algorithms was proposed to solve the sub-problems.

To implement computation offloading in the COO network, many existing works considered utilizing an LEO constellation in space, where each LEO satellite was equipped with an MEC server. In [32], [33], and [34], each user was associated with at most one satellite. In [32], the task offloading decision problem was considered to achieve a minimum energy consumption of the local and edge computing. A distributed algorithm based on the multiplier alternating direction method was proposed, which approximated the optimal solution with low computational complexity. Adopting the same user association method, [33] jointly optimized the task offloading decision and the bandwidth and computation resource allocation. To minimize the weighted sum of the energy consumption and task delay costs, the authors proposed an algorithm based on problem decomposition. Since service placement is preliminary to the computation offloading process, the authors of [34] considered the task offloading problem jointly with the service placement problem. For the minimization of task execution delays, the authors jointly optimized the service placement, task offloading decision and resource allocation of the system. A Lagrange dual decomposition (LDD)-based algorithm was proposed to obtain the closed-form optimal solution, and a heuristic algorithm was also proposed to find an efficient solution with low complexity.

In [35], [36], and [37], the users could offload their computation tasks to multiple satellites simultaneously. The authors of [35] optimized the offloading decision to minimize the weighted sum of the average task response time and the average task energy consumption. They proposed a game-theoretic approach to solve this problem, which reached the

Nash equilibrium in an iterative manner. In [36], joint optimization of task offloading decision and resource allocation was considered in the system. The aim was to minimize the total energy consumption of local and edge computing. The authors proposed a novel algorithm which decomposes the problem into two sub-problems and solves them respectively. In [37], a special system model was considered where the computation task data were generated from source satellites (e.g., Earth observation satellites) and offloaded to satellites with MEC equipment for edge computing. For energy consumption minimization, the task offloading decision and the communication and computation resource allocation were jointly optimized. The authors divided the original optimization problem into two sub-problems and applied successive convex approximation method to design an iterative algorithm.

Some studies further included ISLs in their considered system model, where users' computation tasks are first offloaded to an access satellite and could further be forwarded to other satellites for execution. The authors of [38] proposed a novel task allocation algorithm based on the greedy strategy to optimize the task offloading decision. The algorithm also focused on average delay and energy consumption reduction, and it showed a performance gain over the double edge computation offloading algorithm. In [39], the joint task admission and task scheduling problem was investigated, aimed at jointly minimizing the delay and energy consumption. Utilizing the delayed online learning method based on the Lyapunov framework, the authors developed a practical online distributed algorithm to solve the problem, which could achieve close-to-optimal performance.

Additionally, some studies have considered a more complicated double-layer architecture involving LEO and GEO satellites in space. In [40], each LEO satellite was equipped with an MEC server and executed the offloaded tasks, while the GEO satellites managed and coordinated the satellite MEC resources. To achieve task delay minimization, a scheduling algorithm based on dynamic priority queue was proposed to solve the task offloading decision problem. In [41], the computation tasks could be executed at LEO satellites or GEO satellites. With both latency and energy costs considered, the authors jointly optimized the task offloading decision and communication resource allocation. An improved two-sided many-to-one matching game algorithm was proposed to solve the problem.

Moreover, the combination of the COO structure with ground or aerial networks was investigated. The authors of [42] considered a combined terrestrial-MEC and satellite-MEC network, where an LEO satellite provided edge services in space. In the system, the task offloading strategy and the resource allocation of the satellite were jointly considered, aimed at maximizing the profit of the MEC service provider. The proposed algorithm decomposed the problem into two sub-problems and produced a solution. Focused also on terrestrial-MEC and satellite-MEC combinations, the

TABLE 2. Summary of Advances on the COO Structure

Theme	Ref.	Network architecture	Design objective	Proposed solution
MEC server placement	[27]	LEO constellation with ISLs	Number of placed servers	Design the MEC server placement method by modeling the LEO constellation as a 2D torus network and proposing an algorithm based on the d -hops placement method.
	[28]	LEO constellation with ISLs	Latency	Design the MEC server placement and the association of satellites by a heuristic scheme based on the genetic algorithm.
Service placement	[29]	LEO constellation	Service coverage and robustness	Optimize the service placement by proposing a Lyapunov optimization-based online service placement scheme.
	[30]	LEO constellation with ISLs	Service satisfactory rate and ISL costs	Jointly optimize the service placement and service request scheduling scheme through mixed-integer linear programming.
Computation offloading	[31]	An LEO satellite	Energy	Propose a joint offloading decision and resource allocation scheme based on Lyapunov optimization and deep reinforcement learning.
	[32]	LEO constellation	Energy	Design the task offloading scheme by proposing a distributed algorithm based on the alternating direction method of multipliers.
	[33]	LEO constellation	Latency and energy	Jointly optimize the task offloading decision and the bandwidth and computation resource allocation through problem decomposition.
	[34]	LEO constellation	Latency	Jointly optimize the service placement, offloading decision and resource allocation by an LDD-based algorithm.
	[35]	LEO constellation	Latency and energy	Optimize the task offloading, propose a game-theoretic approach to solve the problem and prove that the Nash equilibrium exists.
	[36]	LEO constellation	Energy	Jointly optimize the task offloading decision and the power, bandwidth and computation resource allocation, and solve the problem through problem decomposition.
	[37]	LEO constellation	Latency and energy	Develop a delayed online learning method under the Lyapunov framework for the joint task admission and scheduling problem.
	[38]	LEO constellation with ISLs	Latency and energy	Propose a novel task allocation algorithm based on greedy strategy.
	[39]	LEO constellation with ISLs	Energy	Jointly optimize the offloading decision of source satellites and communication and computing resource allocation through problem decomposition and successive convex optimization.
	[40]	LEO constellation and GEO with ISLs	Latency	Propose a task scheduling algorithm based on dynamic priority queue.
	[41]	LEO constellation and GEO with ISLs	Latency and energy	Jointly optimize the task offloading decision and communication resource allocation, and propose an improved two-sided many-to-one matching game algorithm to solve the problem.
	[42]	An LEO satellite and a ground base station	Profit of MEC service provider	Jointly optimize the task offloading decision and the communication and computation resource allocation, and solve the problem through problem decomposition.
	[43]	An LEO satellite and multiple ground base stations	Energy	Jointly optimize the task offloading decision and the computing resource allocation, decompose the problem and solve the sub-problems using iterative algorithms.
	[44]	LEO constellation and a UAV	Latency	Design the task offloading decision by proposing a curriculum learning-multi-agent deep deterministic policy gradient approach.
	[45]	An LEO satellite and multiple UAVs	Latency and energy	Jointly design the task offloading decision and UAV trajectory by proposing a multi-agent reinforcement learning based algorithm.
[46]	An LEO satellite and multiple UAVs	Latency, energy and resource cost	Design a hierarchical distributed iterative algorithm to achieve the Stackelberg equilibrium of users' task offloading decisions.	
[47]	LEO constellation and multiple UAVs	Energy	Solve the task offloading decision problem through a deep reinforcement learning algorithm.	

authors of [43] further considered a system model with multiple base stations. To minimize the total energy consumption, the task offloading decision was jointly optimized with the computing resource allocation. The authors adopted the classic alternating optimization method for decomposing the original problem and then solved each sub-problem using low-complexity iterative algorithms.

The authors of [44] considered combining aerial-MEC and satellite-MEC, where users could offload computation tasks to the LEO satellite or to a UAV flying on a predetermined trajectory. The optimization of task offloading decision was conducted to lower the time-averaged task execution latency. To learn the near-optimal offloading strategy, a curriculum learning-multi-agent deep deterministic policy gradient approach was proposed. In [45], the scenario involved multiple UAVs and an LEO satellite, each equipped with an MEC server. The authors jointly optimized the task offloading decision and UAV trajectory to for latency and energy cost minimization. A multi-agent reinforcement learning based task offloading algorithm was proposed to solve the problem. [46] considered a similar network architecture but also included the peer-to-peer (P2P) communication between ground users, allowing computation tasks to be offloaded to peer users for execution. The authors aimed to simultaneously improve the task latency, energy consumption and resource costs by optimizing users' offloading decisions. The problem was modeled as a multi-leader and multi-follower Stackelberg game, and a hierarchical distributed iterative algorithm was designed to achieve the Stackelberg equilibrium. The authors of [47] further considered a system model with multiple LEO satellites and UAVs, equipped with MEC servers, to process or cache users' tasks. The task offloading decision problem was investigated to minimize the energy consumption for task execution. The authors employed a constrained Markov decision process to formulate the task offloading decision problem and further devised a deep reinforcement learning-based algorithm to solve the problem. Table 2 summarizes and compares these works.

D. LESSONS LEARNED AND FUTURE DIRECTIONS

We first compare the MEC server placement problem and the service placement problem in terms of design challenges and solutions. In the former topic, the main difficulty lies in deploying the minimum amount of computing resources while considering the harsh space environment, the limited energy supply, as well as the available ISLs. For service placement, it is challenging to efficiently distribute the service codes and databases under strict constraints on computing and storage resources. Besides, adapting efficiently to the temporal and spatial distribution of user requests is a major challenge for both problems. In terms of potential solutions, heuristic schemes and graph theory-based schemes are widely considered in the MEC server placement problem, while in the service placement problem optimization schemes are often adopted.

Then we present the potential research gaps for the COO structure. First, more realistic scenarios and environments should be considered. For instance, severe electromagnetic radiation in space can influence satellite-based server performance and even cause damage. Therefore, the servers need to be radiation-hardened, which impacts the computation performance. Few existing works have considered this factor. Besides, the energy supply of satellites is heavily dependent on solar power, which can be inconsistent. This also influences satellite-based servers' performance. In future work, these factors should be taken into consideration to obtain more persuasive results.

In addition, a more complicated system model can be investigated. For instance, for the MEC server placement problem, MEC servers can also be placed on GEO satellites in addition to LEO satellites. With their inherently large coverage, the MEC-enabled GEO satellites can not only provide edge computing services for ground users, but also orchestrate the communication and computing resources for LEO satellites, which enables better coordination in the system. This idea has been mentioned in [40] and can be further investigated.

Another direction of research is to choose proper design objectives. We take the service placement problem as an example. In existing studies, the design objective of [30] is service coverage and service robustness, while [29] minimizes the service satisfactory rate and ISL costs. In the future, novel design objectives should be considered to better describe the performance of service placement.

Moreover, some new research topics can be explored. An important instance is the MEC server activation problem. Due to the limited energy on the satellites, adopting a full-on mode for MEC servers may be impractical. Therefore, it is important to decide which of the servers should be activated, in order to satisfy the service requirements and save the energy costs. Different from MEC server placement which is adjusted at similar timescales as infrastructure changes (*e.g.*, months), MEC server activation is often adjusted every few hours or minutes. Network adjustments on this timescale have yet to be investigated. Therefore, a novel network architecture that enables on-demand network adjustments at such a medium timescale needs to be considered [19].

For computation offloading, there are also new research topics to be considered. For instance, the scenario of multiple MEC servers executing a single complicated task can be considered. To achieve this, multiple satellites need to provide edge computing services effectively. The authors of [48] proposed an on-orbit federated learning system, where LEO satellites serve as local servers and a medium earth orbit (MEO) satellite serves as the global server. Further research can be conducted on this topic. Besides, the handover problem of satellite-based MEC servers can be considered. After the edge server finishes computation, the results need to be transmitted back to the user. This can be difficult due to the mobility of the LEO satellites. Many

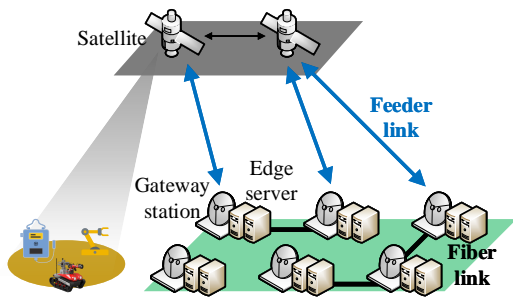


FIGURE 4. Illustration of one possible extension of the CAF structure.

existing works tackle this problem by setting a computation time constraint. However, this might not work when the offloading task is computationally intensive. In that case, the handover of computation results through ISLs is necessary, which can be further investigated.

IV. COMPUTING-AFTER-FEEDER-LINK STRUCTURE

The third minimal structure is the CAF structure. As shown in Fig. 1(c), this minimal integrating structure consists of a satellite, a gateway equipped with an MEC server and multiple IoT devices. The minimal structure can be extended by considering multiple gateways, as shown in Fig. 4.

In this minimal structure, the MEC servers have higher CPU capability, but the time delay for the IoT devices to access the servers is also higher. Therefore, the CAF structure is suitable for wide-area computation-intensive but delay-tolerant applications. Existing studies based on the CAF structure have mainly focused on computation offloading.

A. COMPUTATION OFFLOADING

The authors of [49] considered a system consisting of multiple LEO satellites and a gateway station equipped with an MEC server. To achieve fast and energy efficient offloading, the bandwidth and power resources of users were jointly allocated. The authors introduced a multi-agent architecture in which each LEO satellite made their own allocation policies based on historical policies, as well as users' workload situation provided by an information center. Based on that, a novel multi-agent information broadcasting and judging

algorithm was proposed to allocate resources in a collaborative manner. In [50], a similar system with multiple satellites and a MEC-enabled ground station was considered. The authors considered multiple-input-multiple-output (MIMO) transmission between users and LEO satellites. The user association, offloading decision, MIMO transmit precoding and computing resource utilization are jointly optimized to minimize the long-term average energy consumption. The problem was solved based on Lyapunov optimization theory and problem decomposition, where quadratic transform based fractional programming methods were utilized to solve certain sub-problems.

B. LESSONS LEARNED AND FUTURE DIRECTIONS

Only a few studies investigate the CAF structure, which mainly focus on resource allocation in computation offloading.

For the CAF structure, one possible future direction is the problem of deciding the MEC capability configured for the gateway stations. Since gateways often have sufficient energy provision, the main focus of this problem is to satisfy users' service requirements. This problem can be difficult since that we need to consider not only the service requirement number of the gateways' neighboring areas, but also farther areas that satellites may cover.

In terms of the computation offloading, existing studies [49] only investigated the resource allocation problem. In fact, the offloading decision is also important in this structure, which decides which gateway station the tasks should be offloaded. Offloading may involve ISL transmissions, which makes this problem even more complicated.

V. COMBINATION OF MINIMAL STRUCTURES

After discussing the three minimal structures, possible combinations of the minimal structures and the relevant problems will be discussed in this section.

A. COMBINATION OF CIF AND COO

In Fig. 5(a), one possible combination of the CIF structure and the COO structure is shown. In this section, we review

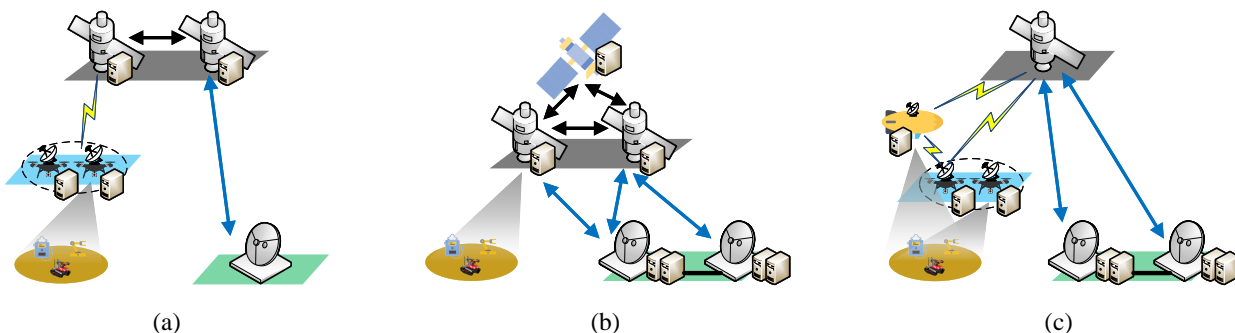


FIGURE 5. Illustration of combinations of minimal structures (a) combination of CIF and COO structure (b) combination of COO and CAF structure (c) combination of CIF and CAF structure [19].

TABLE 3. Summary of Advances on the Combination of CIF and COO Structure

Theme	Ref.	Network architecture	Design objective	Proposed solution
Computation offloading	[51]	An LEO satellite and a UAV	Energy	Jointly optimize the task offloading decision and UAV trajectory by proposing an alternating algorithm based on successive convex approximation.
	[52]	An LEO satellite and a UAV	Energy	Jointly design the task allocation and the UAV trajectory in three scenarios with different satellite availability.
	[53]	An LEO satellite and multiple UAVs	Latency	Jointly design the offloading decision and resource allocation, and propose a solution to the problem based on problem decomposition and the block coordinate descent method.
	[54]	An LEO satellite and multiple UAVs	Energy	Jointly optimize the task offloading decision and resource allocation by proposing a low-complexity algorithm based on successive convex optimization.
	[55]	An LEO satellite and multiple HAPs	Energy	Jointly design the task offloading decision, network resource allocation and MIMO transmit precoding, and propose an algorithm to decompose the problem and solve the sub-problems iteratively.
	[56]	An LEO satellite and multiple UAVs with P2P links	Latency	Jointly design the user association and task offloading decision based on the block successive upper-bound minimization method.
	[57]	LEO constellation with ISLs and a ground base station	Latency/Energy	Optimize the task offloading decision by proposing a double edge computation offloading algorithm based on the Hungarian algorithm.
	[58]	LEO constellation and an HAP	Energy	Jointly optimize the task offloading decision and the communication and computing resource allocation by problem decomposition and an intelligent heuristic algorithm.
	[59]	LEO constellation and a UAV	Latency	Optimize the task offloading decision by proposing a deep reinforcement learning based algorithm.
	[60]	LEO constellation and multiple UAVs	Number of completed tasks	Model the offloading decision problem as a stochastic game and propose a learning-based orbital edge offloading approach to solve the problem.
Service placement	[61]	An LEO satellite and multiple ground base stations	Latency, resource utilization and service caching ratio	Jointly design the service placement strategy, offloading decision and resource allocation by introduced the non-dominated sorting genetic algorithm II.
Content delivery	[62]	An LEO satellite and multiple ground base stations	/	Propose a novel cooperative multicast-unicast transmission scheme to handle both popular requests and personalized requests.

the existing studies focused on the combined CIF and COO structure.

A major part of the existing works focused on the computation offloading problem. In [51], the authors considered a system consisting of a UAV and an LEO satellite, both of which were equipped with an MEC server. The joint task offloading decision and UAV trajectory design problem was investigated to minimize the total energy consumption. The authors proposed an alternating algorithm based on the successive convex approximation approach to solve the problem. The authors of [52] considered a similar system with an MEC-enabled UAV and an LEO satellite, but further discussed three different scenarios according to the availability of satellite communication. In each scenario, the task allocation was jointly designed with the UAV trajectory to

minimize the total energy consumption based on successive convex approximation strategies.

Other works considered a more complicated system, consisting of a satellite and multiple UAVs or HAPs with MEC server equipment. The authors of [53] considered a latency-oriented joint offloading decision and resource allocation problem in the network. The authors proposed a solution to the problem by decomposing the problem and utilizing the block coordinate descent method. In [54], the authors also investigated the task offloading decision and resource allocation in this network, but turned to minimize the total power consumption of the satellite, UAVs and users. A low-complexity algorithm based on successive convex optimization was proposed to solve the problem. In [55], the system consisted of an LEO satellite and multiple HAPs. Specially, the user-HAP and HAP-LEO communication links all

adopted multiple-input-multiple-output (MIMO) techniques. In this paper, the task offloading decision and the network resource allocation were jointly designed with the MIMO transmit precoding. The aim was to minimize the total energy consumption of communication and computation in the system. The authors proposed an algorithm to decompose the problem and solve the sub-problems iteratively. In [56], the authors considered that the UAVs could communicate with each other, so that users' computation tasks could be offloaded among the UAVs for better execution. The user association and offloading decision were jointly optimized to minimize the sum of users' task latency. The problem was non-convex, and thus the block successive upper-bound minimization method was proposed as a solution.

In addition, some studies considered the scenario of utilizing multiple satellites in space. In the system model of [57], users offloaded their task data to a ground base station for edge computing. The data could further be offloaded to an access satellite and transmitted to other satellites through ISLs for data processing. To allocate users' tasks, the authors proposed a double edge computation offloading algorithm based on the Hungarian algorithm. This proposed algorithm could minimize respectively the average task latency and the average energy consumption of edge servers. In [58], an HAP collected and processed users' task data. Distinguishing from [57], the HAP could further offload the task data to multiple satellites simultaneously for edge computing. The task offloading decision and the communication and computing resource allocation were jointly optimized to achieve energy-minimization in the system. The authors decoupled the problem and proposed an intelligent heuristic algorithm for solution. Moreover, [59] jointly considered the CIF and COO combined network with the terrestrial MEC network. Specifically, a UAV with MEC equipment collected users' computation tasks. The tasks could be executed at the UAV-based server, or offloaded to ground-based or satellite-based servers. The optimization of the offloading decision was performed to minimize the average execution latency. The problem was formulated into a Markov decision process, which was solved by a deep reinforcement learning based algorithm. In [60], the authors further considered a network consisting of multiple MEC-enabled UAVs as well as MEC-enabled LEO satellites. Ground users offload their tasks to the associated UAV, and the UAV process the task data or further offload them to certain satellites for processing. The authors aimed to maximize the number of tasks that were completed before the deadline by designing the task offloading decision. The problem was modeled as a stochastic game and a learning-based orbital edge offloading approach was proposed to solve the problem.

The authors of [61] took a step further to jointly consider service placement and computation offloading in a combined CIF and COO network. Specifically, some users in the system offloaded not only their task data but also the corresponding execution codes. The execution codes were cached

in ground-based or satellite-based servers, which could then handle offloaded tasks of the same service type. The service placement strategy, offloading decision and resource allocation were jointly optimized in the network. The aim was to minimize the system cost, which was a weighted sum of task latency, computation resource utilization, bandwidth utilization and cache ratio. The authors introduced the non-dominated sorting genetic algorithm II to solve the problem.

The authors of [62], on the other hand, focused on the content delivery problem. They considered a network where MEC servers were placed on the satellite and ground base stations. A novel cooperative multicast-unicast transmission scheme was proposed to handle both popular requests and personalized requests. Table 3 gives a summary of all these works.

B. COMBINATION OF COO AND CAF

In Fig. 5(b), one possible combination of the COO structure and the CAF structure is shown. In this section, we review the existing works considering a combined COO and CAF structure.

We first summarize the studies focused on the computation offloading problem. Some studies considered a simple system model which consisted of an LEO satellite and a ground gateway station, both equipped with an MEC server. The authors of [63] jointly optimized the task offloading decision and the bandwidth allocation of user-satellite and satellite-gateway links, to minimize the weighted sum of task execution latency and energy consumption. The authors proposed a deep reinforcement learning-based algorithm to solve the problem, which could achieve near-optimal offloading cost performance with low computation complexity. In [64], joint optimization of task offloading decision and resource allocation was performed to minimize the time-averaged task execution latency. The authors leveraged the framework of Lyapunov optimization to convert the problem into multiple sub-problems, which were then solved in an iterative manner.

Further studies were conducted which focused on utilizing multiple satellites in space and a single gateway station. Assuming each user was associated with a single satellite, the authors of [65] jointly optimized the offloading decision and bandwidth allocation, aimed at both latency and energy costs. A distributed deep learning algorithm was introduced to solve the problem in two stages. Adopting the same user association scheme, [66] investigated the computation offloading of two types of computation tasks, namely edgy-cloud and cloudy-edge. Joint optimization of offloading decision and computation resource allocation were considered for each user to reduce the system costs. Specifically, the system costs took delay, energy consumption, and resource utilization into consideration. The authors provided a game-based perspective on the problem and proposed a hybrid particle swarm optimization-based algorithm to achieve the Nash equilibrium. [67] also investigated a system consisting

TABLE 4. Summary of Advances on the Combination of COO and CAF Structure

Theme	Ref.	Network architecture	Design objective	Proposed solution
Computation offloading	[63]	An LEO satellite and a gateway station	Latency and energy	Jointly optimize the task offloading decision and the bandwidth allocation by proposing a deep reinforcement learning-based algorithm.
	[64]	An LEO satellite and a gateway station	Latency	Jointly optimize the task offloading decision and allocation, and solve the problem by leveraging the framework of Lyapunov optimization to convert the problem into multiple sub-problems.
	[65]	LEO constellation and a gateway station	Latency and energy	Jointly optimize the task offloading decision and bandwidth allocation, and solve the problem in two stages by a distributed deep learning algorithm.
	[66]	LEO constellation and a gateway station	Latency, energy and resource utilization	Jointly optimize the task offloading decision and computation resource allocation by adopting a game-based perspective, and propose a hybrid particle swarm optimization-based algorithm to achieve the Nash equilibrium.
	[67]	LEO constellation and a gateway station	Energy	Jointly optimize the user association, offloading decision and communication resource utilization and solve the problem by problem decomposition.
	[68]	Three LEO satellites with ISLs and a gateway station	Energy	Jointly optimize the task offloading decision and computation resource allocation based on the improved non-dominated sorting genetic algorithm II.
	[69]	LEO constellation with ISLs and a gateway station	Latency and energy	jointly optimized the task offloading decision and computation resource utilization by designing a deep reinforcement learning method based on proximal policy optimization.
	[70]	LEO constellation with ISLs and a gateway station	Energy	Optimize the inter-satellite routing scheme jointly with the task offloading decision and transmission power, and solve the problem by a two-stage algorithm.
	[71]	LEO constellation with ISLs and a gateway station	Latency and resource utilization	Jointly optimize the task offloading decision and the communication resource utilization, and solve the problem by decomposing it into two sub-problems.
Computation offloading and content delivery	[72]	LEO constellation and multiple gateway stations	Latency and energy	Jointly design the task offloading decision and resource allocation by proposing a solution based on deep reinforcement learning.
	[73]	LEO constellation and GEO/MEO with ISLs, and a gateway station	Latency and resource utilization	Jointly Design the task offloading decision and caching decision by proposing a deep imitation learning-driven offloading and caching algorithm to achieve real-time decision making.

of multiple MEC-enabled LEO satellites and an MEC-enabled gateway station, but in the system users could offload their task data to multiple satellites. The authors jointly optimized the user association, task offloading decision and communication resource utilization, aimed at minimizing the overall energy consumption. The problem was decomposed into four sub-problems and solved based on relaxation transformation and fractional programming. Some studies further included ISLs in the system model, where task data could be transmitted between satellites through ISLs. In [68], the authors considered a simple scenario with an access satellite and two nearby satellites. Joint task offloading decision and computation resource allocation were conducted for energy consumption minimization. The authors provided a solution

to the problem based on the improved non-dominated sorting genetic algorithm II. A more complicated system model which utilized an LEO constellation with ISLs in space was further explored [69]. The authors jointly optimized the task offloading decision and computation resource utilization, aimed at lowering both the task execution latency and energy costs. A deep reinforcement learning method based on proximal policy optimization was designed to approximate the optimal solution. Considering a similar network, the authors of [70] optimized the inter-satellite routing scheme, jointly with the task offloading decision and the transmission power. The objective was to minimize the energy consumption at the satellites while fulfilling latency constraints. The authors proposed an algorithm which decomposed the problem and

solved it in two stages. In [71], a computation task was modeled as a directed graph consisting of multiple virtual network functions. These virtual network functions could be uploaded to different satellites through user-satellite links or ISLs for execution. Joint optimization of offloading decision and communication resource utilization was conducted for bandwidth and delay cost minimization. A distributed algorithm based on multi-agent systems was proposed, which achieved better system performance than the Viterbi and game theory algorithms.

Moreover, a more complicated system could be considered, which consisted of multiple LEO satellites and multiple gateway stations, each with an attached MEC server [72]. The authors investigated the joint task offloading decision and resource allocation problem in the network, with the aim of improving system latency and on-orbit computing energy consumption. A solution based on deep reinforcement learning was proposed for this problem.

On the other hand, the authors of [73] jointly considered the computation offloading and content delivery problem. Specifically, the computation tasks could be executed on satellites or at the gateway, and the results could be cached on satellite-based servers for further reuse. Joint optimization of task offloading decision and caching decision was performed, aiming to improve both the latency performance and the resource utilization in the system. To this end, the authors proposed a deep imitation learning-driven offloading and caching algorithm which could achieve real-time decision making. Table 4 summarizes and compares these works.

C. COMBINATION OF CIF AND CAF

In Fig. 5(c), one possible combination of the CIF structure and the CAF structure is shown. Very few studies have focused on the combination of the CIF structure and the CAF structure. The authors of [74] considered a system with multiple ground base stations, a satellite and a gateway, where MEC servers were deployed at the base stations and the gateway. The users' task data could be offloaded to an associated base station, or further to the distant gateway with stronger computing capability through satellite communication. The task offloading decision was jointly optimized with the communication and computation resource allocation to minimize the task execution delay. The authors divided the problem into two sub-problems, where the task offloading decision subproblem was solved with theoretical analysis and mathematical derivation, and the resource allocation problem was solved by utilizing the particle swarm optimization algorithm. In [75], the authors considered a system consisting of an LEO satellite that connects to the computing server at the gateway station and multiple MEC-enabled UAVs. The UAV trajectory and communication resource allocation were jointly optimized for energy minimization, and the problem was solved leveraging an iterative algorithm.

D. LESSONS LEARNED AND FUTURE DIRECTIONS

By deploying multiple layers of MEC servers, the combined structures could incorporate the advantages of basic structures and therefore support more demanding service requirements. However, for the combined network structures, new system design challenges will arise since the network architecture is more complicated. We select two of the combined structures as examples to discuss their advantages and challenges compared to basic structures.

The combined CIF and COO structure deploys MEC servers on both APs and satellites. Compared with the CIF structure, the task data of IoT devices could not only be offloaded to UAVs/HAPs for local applications, but also aggregated with other users' data at the satellite-based server for execution, which further support wide-area applications with relatively low latency. Besides, compared to the COO structure, the combined structure allows the task data to be pre-processed at the APs to reduce the data size by extracting key information. This enables more efficient utilization of communication and computing resources, as well as reduce the task latency. Nevertheless, this combined structure also faces new challenges. For instance, the multi-tier computing resources render the offloading decision problem more difficult. Besides, both UAVs and LEO satellites could be highly mobile, leading to a dynamic network architecture. This also adds to the difficulty of system design.

For the combined COO and CAF structure, MEC servers are deployed on satellites as well as at gateway stations. This combined structure could usually empower more computation-intensive applications than the COO structure, since satellites are often strictly limited in computing resources. Compared with the CAF structure, on the other hand, it enables that the application data generated on satellites (e.g., remote sensing data) could be offloaded through ISLs for low-latency processing. Such combination also raises new challenges, such as how to efficiently distributing task data among satellites and gateways through ISLs and high-speed feeder links.

Furthermore, we note that for these structures, some existing works study a simple network architecture by considering a single satellite, while other works further consider multiple satellites in the system. Extending a single satellite to multiple satellites raises new system design challenges. First of all, the offloading decision problem naturally becomes more complicated since more than one satellite is equipped with an MEC server. In addition, ISLs among satellites need to be considered in a satellite constellation, which have different characteristics compared with other communication links in the network, such as ground-to-space links and feeder links. This renders the joint orchestration of heterogeneous communication and computing resources more difficult. Besides, handover among satellites as well as coordination among satellites for task data processing are also important challenges in the multi-satellite architecture.

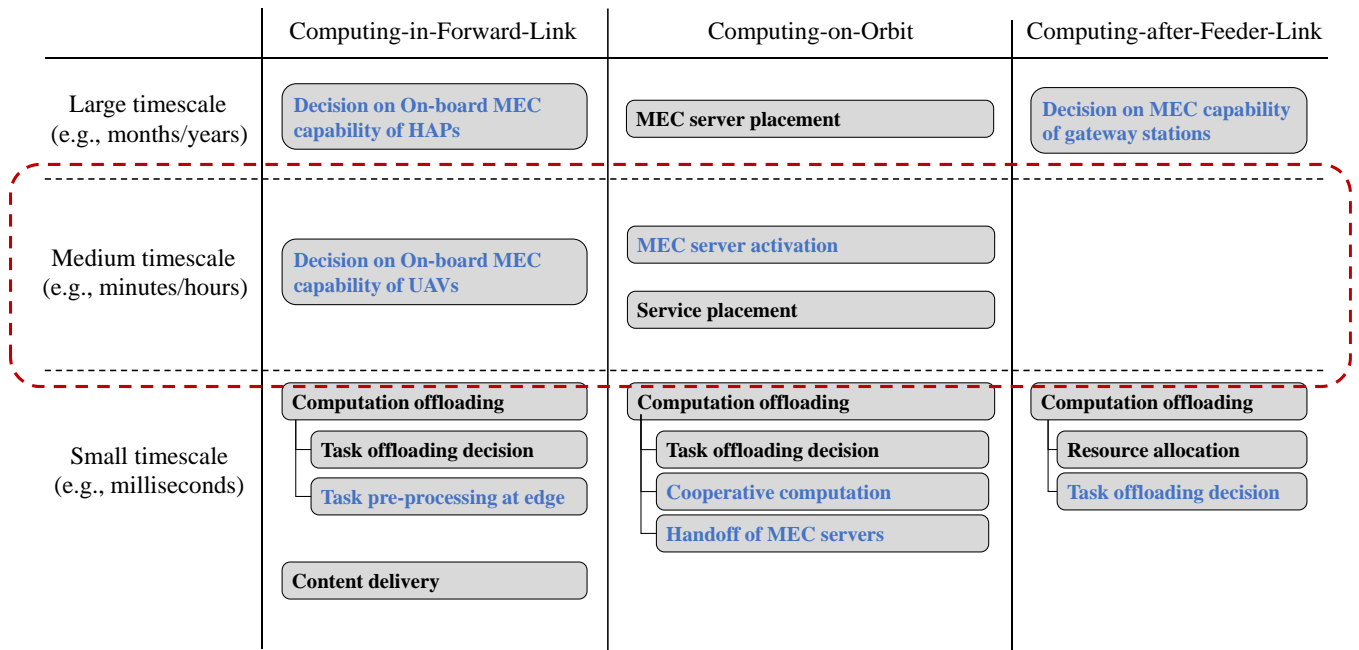


FIGURE 6. Existing and future research directions of the three basic structures at different timescales. (The blue-colored topics are yet to be discussed.)

VI. OPEN RESEARCH ISSUES

This section outlines a few open research issues in the integration of satellite and MEC.

A. HIERARCHICAL ORCHESTRATION OF MINIMAL STRUCTURES IN THE INTEGRATED SATELLITE-MEC NETWORK

The scale of a practical integrated satellite-MEC network is often huge, and the network consists of a massive amount of minimal structures. These minimal structures are often strongly coupled in terms of resource utilization (e.g., communication bandwidth) and task division, which renders the system design complicated. Inspired by the structure of proteins, we believe that adopting a hierarchical minimal structure orchestration framework could be a promising solution. Specifically, minimal structures can be simply orchestrated into secondary structures (amino acids orchestrated into peptides), which further form more complicated tertiary structures (larger peptides), and so forth. Eventually, these structures form highly functional integrated satellite-MEC networks (proteins). In this framework, the system design of a tertiary structure, for instance, could directly utilize the secondary structures as basic elements for network orchestration, without going into the details of the lower-level minimal structures. Therefore, the computation complexity of network orchestration could be significantly reduced. Further researches into this hierarchical orchestration framework could be considered.

B. HIERARCHICAL-TIMESCALE NETWORK ADJUSTMENTS IN THE INTEGRATED SATELLITE-MEC NETWORK

The current network is mainly adjusted or optimized at two timescales. Network planning and network architecture adjustment often take place at a large timescale (e.g., months or years). Specific communication and computation parameters are adjusted at a small timescale (e.g., milliseconds). For the integrated satellite-MEC network, service requirements' number, service type and spatial distribution change dynamically at a timescale in between. Thus, the traditional network adjustment is unable to match the service requirements, resulting in degraded resource efficiency. Therefore, a hierarchical-timescale network adjustment framework is of interest. We categorize in Fig. 6 the existing and future research topics, based on a hierarchical-timescale framework. It can be observed that for each minimal structure there exist many problems of medium-timescale network adjustment to be explored. Moreover, since the medium timescale is usually much larger than the channel coherence time, a process-oriented optimization framework could be considered for the design of network adjustments [76].

C. AI-BASED INTEGRATED SATELLITE-MEC NETWORK

AI-based tools and methods have been widely used recently. AI-based methods can be applied to the integrated satellite-MEC network in two aspects. First, the integration of satellite and MEC raises new problems, some of which may be hard to model. In this context, AI-based methods can be utilized to provide a feasible solution. In fact, many learning-based schemes have been utilized in existing studies. For instance,

in [37] a delayed online learning method was developed for task admission and scheduling. Besides, many existing studies considered adopting a deep reinforcement learning-based algorithm [47] [59] [69] [72]. On the other hand, the widely distributed MEC servers with close proximity to users can support AI-based applications in return. In fact, [48] considered utilizing MEO and LEO satellites to implement a federated learning network. Further investigations into both aspects can be considered.

D. SECURITY ISSUES IN THE INTEGRATED SATELLITE-MEC NETWORK

Security is an important issue for the integrated satellite-MEC network. Satellite networks provide coverage for a wide geographical area. The openness of electromagnetic environment makes the network susceptible to cyber-attacks of different types, such as eavesdropping and jamming. Besides, the sophisticated integration of satellite and MEC recalls novel system design methods, which may also raise new security risks. To address these problems, new security measures need to be designed and implemented in the network. One possible solution is to combine the integrated satellite-MEC network with the blockchain technique, where each MEC server can work as a node in the blockchain network. However, this may require massive data transmission for data synchronization, which can be difficult for the integrated satellite-MEC network. This tradeoff between security and resource utilization can be further investigated.

E. INTEGRATED SATELLITE-MEC NETWORK COORDINATED WITH REMOTE SENSING

In addition to ground IoT devices, the satellites for remote sensing also generated a great amount of data that needs to be processed. By deploying integrated satellite-MEC networks, the remote sensing task data could be computed at the network edge, which reduces the task latency and saves the communication resources for offloading to the remote cloud. In fact, several existing studies have investigated this issue. The work [28] has considered a simple coordination scenario where the computation tasks generated by the satellite itself and offloaded by ground users are processed together. In [37], the offloading decisions of source satellites are jointly designed with the satellite-MEC network's communication and computing resources. Nevertheless, there still exist many research gaps that require further consideration, such as distributing the task data efficiently through ISLs in the satellite constellation. Moreover, the coordination could be further investigated to achieve functional cooperation in an efficient manner, where new applications that require joint sensing-communication-computation capabilities can be enabled.

F. GREEN INTEGRATED SATELLITE-MEC NETWORK

In the integrated satellite-MEC network, a huge number of MEC servers will be deployed in a hierarchical manner to provide services, which leads to massive energy consump-

tion. Besides, UAVs, HAPs and other vehicles (automated or manual) are widely adopted in the integrated satellite-MEC network, which also leads to substantial energy consumption and carbon emissions. Therefore, it is important to develop a green integrated satellite-MEC network. Traditional methods used in the terrestrial networks may not be applicable, because servers and vehicles in the integrated network are highly mobile and distributed sparsely and heterogeneously in wide area. Novel techniques for a greener network can be interesting.

G. SUPPORTING SENSING-COMMUNICATION-COMPUTING-CONTROL CLOSED-LOOP DESIGN WITH THE INTEGRATED SATELLITE-MEC NETWORK

Certain mission-critical IoT applications require the tasks executed in a sensing-communication-computing-control (SC³) closed-loop manner [77]. Specifically, the sensors collect information on the field and transmit the sensing data to the computing server. The server processes the sensing data to make decisions, which are further transmitted to the field robots for execution. Since these applications could take place in remote or rural areas while require low-latency closed-loop control, supporting them with integrated satellite-MEC networks is a potential solution. To this end, the data scheduling and resource orchestration in the integrated satellite-MEC network needs to be designed for control-oriented optimization, which requires further discussion.

VII. CONCLUSIONS

In this paper, we have captured the latest technical advances in satellite-MEC integration. Specifically, we have classified the existing studies based on three minimal structures. For each minimal structure, we have presented a comprehensive literature review based on the research topics, and have further discussed the gaps and research directions. In addition, we have also reviewed the studies that focus on the combination of minimal structures. Finally, we have outlined the open issues for satellite-MEC integration, such as introducing a hierarchical-timescale network adjustment framework to improve resource efficiency, and combining the integrated network with AI-based techniques, blockchain-based security measures, as well as sensing and navigation functions.

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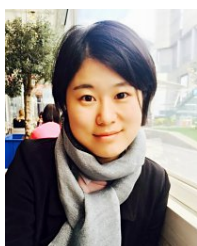
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