Enabling Resilient Access Equality for 6G LEO Satellite Swarm Networks

Shih-Chun Lin, Chia-Hung Lin, Liang C. Chu, and Shao-Yu Lien

Abstract

Low earth orbit (LEO) mega-constellations, integrating government space systems and commercial practices, become enabling technologies for the sixth generation (6G) networks due to their excellent merits of global coverage and ubiquitous services for military and civilian use cases. However, convergent LEO-based satellite networking infrastructures lack leveraging the synergy of space and terrestrial systems. This paper extends conventional cloud platforms with serverless edge learning architectures for 6G satellite swarm ecosystems and provides a new distributed training design from a networking perspective. The proposed method dynamically orchestrates communications, computation functionalities, and resources among heterogeneous physical units to efficiently fulfill multi-agent deep reinforcement learning for service-level agreements. Innovative ecosystem enhancements, including ultra-broadband access, anti-jamming transmissions, resilient networking, and related open challenges, are investigated for end-to-end connectivity, communications, and learning performance.

Introduction

Low earth orbit (LEO) mega-constellations [1–3] with government and commercial satellites have been regarded as the most promising remedy to provide global coverage and ubiquitous wireless services, bridging the ever-existent digital divide via their global footprints. These satellite swarms, comprising small distributed satellites in lower orbits via optical inter-satellite links, provide less latency and overlapping coverage for broadband connectivity without suffering geographical limitations [1]. Satellite swarm networks can leverage ground station control and autonomous multi-satellite operations to form different flying patterns (e.g., trailing, cluster, or constellation) and enable resilient access equality, depending on separating satellites and intended applications. Meanwhile, emerging distributed machine learning (ML) brings attention to decentralized data sources. This learning technology will likely address multi-dimensional resource allocations for integrated satellite swarms and the sixth generation (6G) networks. However, existing multi-satellite solutions mainly assume their system feasibility and directly work on enabling applications (e.g., [2]). There is little investigation into the redundancy and tradeoff between computations and communications and the dedicated resource orchestrations to realize timely edge learners with efficient data processing. Few solutions exist to comprehensively evaluate distributed training performance concerning the peculiarities of satellite swarm networks (e.g., satellite access and multi-tier connected infrastructure). Architectural, operational, and management changes are a must for such ecosystems.

Recent studies focus on integrating satellite swarms with ground communications and reveal the spectral efficiency of non-terrestrial coexistence via ML-based resource allocation. An automatic network slicing platform for the Internet of space things is presented in [1], which carries out service-level agreements (SLAs) over the space-ground integrated infrastructure. In [2], beamspace MIMO (multiple-input multiple-output) is exploited for downlink satellite swarms, requiring only position information for distributed linear precoders and a ground equalizer. In [3], optimal network control structures are studied to improve the temporal control effectiveness with the least number of controllers. Authors in [4] consider three-dimensional terrain surface coverage by designing hierarchical unmanned aerial vehicles (UAVs) swarms via deep reinforcement learning (DRL) algorithms. A multi-tier collaborative DRL scheme is proposed in [5] to empower resource allocation in satellite-aided vehicular networks.

Regarding edge applications, function as a service (FaaS) models emerge to decompose the application into functions invoked individually or in a chain [6]. FaaS is suited to the practical interest of the event-based programming model (microservices or serverless), efficient resource (at the device- and edge-level) utilization, and high system scalability. In [7], a survey of ML-enabled microservices is provided to leverage heterogeneous, distributed, and resource-constrained edge computations for secure Internet of Things (IoT) networks. In [8], serverless computing implementation is integrated into edge computing scenarios, and comprehensive overviews of architecture designs and challenges are given. Resilient edge access and coexistence and resource management developments for 6G satellite swarms are in their infancy and require innovations and new approaches.

This article presents a serverless software-defined networking (SDN) architecture that dynamically orchestrates communications and computation resources for a diverse set of 6G SLAs. A serverless edge platform is established that orchestrates function containers among (geographically distributed) ML-SDN control engines in space and ground tiers for highly flexible, virtualizable SDN infrastructure. The above applications only need to care about function implementation without managing any underlying resources. This unified control platform can alleviate the disturbance to physical infrastructure units giving time-varying resource availability and heterogeneity. It also allows a multi-tier ML framework to optimize networking and resource configurations according to each tier's practical constraints, such as heterogeneous computing capabilities of SWaP (size, weight, and power)-limited satellites and ground stations, frequently-handover satellite access, and coverage-limited ground tier. Remarkably, the intelligence within multiple ML-SDN control engines (e.g., ground stations and satellites with computing capabilities) can realize efficient broadband access for ground users concerning software-reconfigurable LEO satellites, data-driven approaches for unknown environments, and differ-

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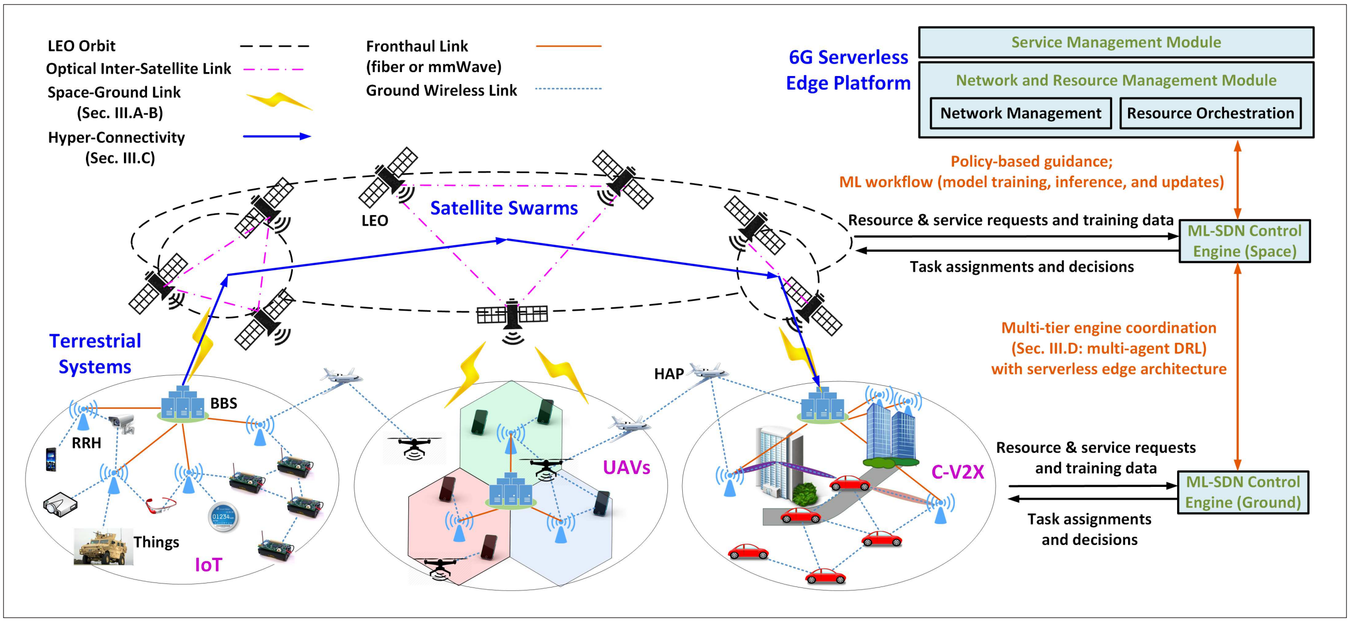

FIGURE 1. A serverless edge architecture with ML-SDN engines and enabling technologies for 6G LEO swarm networks.

ent decision timescales of each unit. As a result, the designed multi-tier ML models create high-throughput, reliable end-to-end transmissions for global connectivity. The proposed architecture and solutions bring many benefits to 6G satellite swarm ecosystems, as listed below:

1. We provide **a serverless SDN edge architecture** that introduces a serverless computing layer based on an abstraction of the ground-space ecosystem. Both application programming interfaces (APIs) and network resource management tools are developed to manage applications on-demand through dynamically instantiated containers and effectively utilize computing resources from distributed satellites and ground stations.
2. We improve **the end-to-end learning performance** by dynamically adjusting workloads among ML-SDN control engines. For example, ground stations with powerful computing capabilities can assist satellites' resource allocation tasks. The satellite learning model can also be transferred to its successor, preventing always training from scratch for SWaP-limited devices.
3. We enable **data-driven multi-user access control** for the ground-space eco-network. Serverless computing architectures provide infrastructure controllability to the multi-tier ML models, establishing efficient ultra-broadband sensing and communications to satisfy 6G requirements.
4. We achieve **reliable software-defined internetworking** through spectrum harmonization and hyper-connectivity. New networking designs are realized to address heterogeneity, scalability, performance, and reliability fully.

Therefore, our innovations significantly enhance end-to-end performance and impact future human society in isolated or remote communities and landlocked areas with limited infrastructure investments. Our designs facilitate distributed deep training development with fast adaptiveness and efficient multi-tier processing while tackling non-terrestrial system heterogeneity and dynamics. It is noteworthy that this work tightly aligns with the latest industry specifications. For instance, 3GPP Release 17 considers satellite mobility at different orbital heights to support non-terrestrial networks with 3GPP NR (new radio) on the ground. Release 18 creates 5G Advanced, including new intelligent, ML-enabled solutions to boost mobile broadband and verticals performance.

The rest of this article is organized as follows. The following section gives our serverless edge architecture. We then investigate LEO-based ultra-broadband access and resilient networking. Following that, open research problems are discussed. The final section concludes the article.

Serverless Edge Architecture with Multi-Tier ML-SDN Control Engines

Figure 1 shows the proposed serverless edge architecture in ground and space tiers for 6G satellite swarm networks. The ground tier consists of several terrestrial systems, such as the IoT, UAVs, and cellular vehicle-to-everything (C-V2X); each system has a dedicated ML-SDN control engine. The control engines integrate SDN controllers with ML algorithms and manage computing, storage, and communications resources. They receive resource and service requests and training data from the serving systems and, in turn, assign tasks and control decisions back. The space tier includes satellite swarms from operators, such as SpaceX, Amazon, Telesat, and the space development agency (SDA), in orbits and operating systems. A serverless edge platform is built for a scalable and unified control plane to coordinate multi-tier engines and constitutes a shared resource pool for virtualization and network slicing. As shown in Fig. 1, this platform gives policy-based guidance for ML workflows and effectively manages resources via two crucial modules to meet diverse SLAs simultaneously for an intelligent networking architecture.

First, the service management module enables emerging satellite and ML applications to request SLA portfolios (e.g., link throughput, end-to-end latency, etc.) from the lower management module. Each application is decomposed into functions (e.g., service discovery, deployment, scheduling, caching, etc.) and defines a dedicated service function chain upon the infrastructure. Second, the network and resource management module collects global network status, allocates multi-dimensional resources, and regulates multiple control engines with the ML deployments. Specifically, network management maintains the topology, decides the best routes, and schedules and monitors the upper function chains. Resource orchestration allocates and controls underlying resources from distributed infrastructure. Hence, the platform can efficiently explore network adaptiveness and realize optimal space-ground policies at the edges through network automation.

The 6G serverless edge platform pushes the controllability to network edges via local control engines with edge and serverless computing. A single centralized control with huge decision parameters for 6G satellite swarm networks to cover an ultra-wide geographical and spatial area is not feasible. Table 1 summarizes three control plane implementations, cor-

ML-SDN infrastructure	Attribute	Challenge	Learning deployment/use case
Distributed control	Each ML-SDN control engine regulates its domain	No cooperation, no centralized control	Individual structure [2–4, 9. 10]
Multi-domain control (flat)	Engines can cooperate with others	Signaling overheads among engines	Federated/global structures [1, 5]
Multi-layer hierarchical control	Software-defined hierarchy & load balancing	More sophisticated control policies	Federated/hierarchical/global structures [4]

TABLE 1. Edge networking infrastructures and multi-agent learning deployments.

	sub-6GHz		mmWave		THz	
	[9]	[10]	[9]	[10]	[9]	[10]
Mean square error	0.003	0.069	0.002	0.022	0.001	0.019
Cosine similarity	0.995	0.337	0.996	0.646	0.991	0.439
Structure similarity	0.852	0.303	0.931	0.739	0.939	0.629
Detection rate	90%	–	97%	1.6%	94.5%	6.2%
F_1 score	94.7%	–	98.5%	3.2%	97.1%	11.7%

TABLE 2. ML-enabled ultra-broadband sensing schemes (i.e., ours [9] versus GAN [10]) for the ground tier's C-V2X.

responding attributes, challenges/costs, and learning deployments for multi-tier ML-SDN engines. These multiple engines can be organized in a fully distributed, multi-domain flat, or multi-layer hierarchical manner to provide control scalability and boost learning efficiency. The multi-domain and multi-layer control can realize optimal global learning by splitting enormous optimization dimensions into collaborative engines' tasks. Such collaboration can be revamped from SDN's east-bound and west-bound APIs. The south-band APIs are expanded to help ML-SDN engines communicate and control the underlying physical resources. The developed designs are dedicated to systems' functions, such as satellite beam steering, UAV movement control, and resource block allocation in base stations. For example, our multi-domain control realization [5] facilitates resource allocation decision-making concerning different computing capabilities of ground vehicles and satellites and confirms its effectiveness via comprehensive V2X simulations.

Enabling Technologies: LEO-Based Access, Networking, and Multi-Agent Deep Learners

This section investigates enabling technologies for serverless satellite swarm networks. These include sensing-enabled coexistence on ML-SDN engines, resilient beyond-line-of-sight access for resource orchestration, novel space corridor via service and network management, and multi-agent DRL deployment for multi-tier ML-SDN engine coordination.

Automatic Ultra-Broadband Spectrum Sensing

Conventional software-defined satellite networks allow beam transmissions via certain bands, e.g., DVB-T (174 MHz to 786 MHz) in most satellite systems. Recent beyond-line-of-sight communications also advance in higher frequency bands, such as C-band (4 GHz to 8 GHz), Ku-band (12 GHz to 18 GHz), and Ka-band (27 GHz to 40 GHz), concerning their higher data rate transmissions. For example, in NASA's remote sensing and earth exploration services, their Aura satellites collect radiometric data on 118 GHz, 190 GHz, and 2.5 THz. For ground transmissions, 5G NR considers frequency ranges 1 (sub-6GHz) and 2 (millimeter wave, mmWave) in Release 17 to support C-V2X communications for wide-area coverage. Hence, given that all these transmissions can happen concurrently and the latest transceiver hardware advances, it is assumed that next-generation terrestrial base stations should be able to recognize these spectrum usage behaviors over the ultra-broadband spectrum soon. How to sense and identify spectrum usages in such ultra-broadband is crucial and necessary for enabling LEO-based access in an integrated terrestrial and non-terrestrial environment. A frequency-agile ultra-broadband reconfigurable frontend is envisioned to realize full-spectrum (1 GHz to 10 THz) sensing and communications that meet data rate, reliability, and scalability requirements. Spectrum innovation technology and sensing-informed dynamic access to all-spectral resources will harmonize the 6G satellite swarm network spectrum.

In serverless edge architectures, the network infrastructure and ground terminals can utilize ML-SDN control engines and end-to-end learning algorithms to

- Recognize *all-spectral* usage
- Exploit radio resources for communications efficiency.

First, evolving from MHz to GHz spectrum characterization, wireless learning features (e.g., signal waveforms, cyclic spectrums, complex correntropy) can be extracted from raw sensory input. Learning-based wideband sensing techniques (e.g., wavelet detection, compressed sensing) can be designed to identify available spectrums effectively. Under practical wireless channels (e.g., fast fading for highly mobile vehicles), real-time learning variants (e.g., real-time inference, fast spectrum analytics) can be further investigated for timely sensory processing. We evaluate a C-V2X system with co-existing sub-6 GHz, mmWave, and THz communications in the ground tier by setting up a realistic environment from downtown Raleigh via SUMO (Simulation of Urban MObility). The transportation parameters are 600 m^2 area, 5×1.8 m^2 vehicle size, 2.5/s vehicle arrival rate, and 55.56 m/s maximum vehicle speed. All-spectral communications parameters are set as sub-6GHz (0–2 GHz operating frequency, 2 GHz bandwidth, 100 m coverage, 0 dBi antenna gain), mmWave (26.5–29.5 GHz frequency, 3 GHz bandwidth, 15 m coverage, 20 dBi gain), THz (100–550 GHz, 450 GHz, 15 m, 50 dBi), 256 subcarriers, eight maximum connections, one subcarrier guardband size, 30 dB signal-to-noise ratio (SNR), and 0.125 Nyquist rate. Upon this setup, Table 2 shows the performance of ultra-broadband spectrum recognition and sensing for our work [9] and a recent generative adversarial network (GAN)-based solution [10]. The results imply that our scheme can effectively learn multiple simultaneous connections and outperforms the GAN realization for all bands by jointly designing spectrum compression and reconstruction.

Based on the time series of ultra-broadband sensing results, the ML-SDN engines can further employ deep recurrent learning (e.g., long short-term memory, gate recurrent unit) and DRL algorithms to develop dynamic all-spectral access. The corresponding spectrum decision, sharing, and mobility can be proposed to avoid radio interference between ground and space tiers. The sensing-enabled coexistence can optimize shared spectrum allocation by considering delayed sensing data. Accordingly, ML-SDN control engines can devise an autonomous frontend that tunes optimal configurations (e.g., analog electronics, bandwidth sensitivity, position) to harmonize ultra-broadband spectrum access in real-time.

Adaptive Beyond-Line-of-Sight Communications

Since LEO satellites provide less uplink/downlink latency, optimizing beyond-line-of-sight communications become feasible. Resource orchestration in the serverless platform can develop adaptive modulation and coding and power control mechanisms in higher bands to realize efficient ground-LEO access, particularly for uplink communications as 6G backhaul or integrated access and backhaul. Ka-band systems (currently applied by Starlink Gen. 2) deliver substantially greater throughput than previous Ku-band offerings. ML-SDN control engines can operate adaptive communications parameters by employing satellite channel estimation and a feedback control loop. Figure 2 shows downlink packet error rates for an LEO satellite to a beyond-line-of-sight ground station. Ten stations share the channel via direct sequence spread spectrum (DSSS) with 240 (i.e., 23 dB) spreading factor, Raised Cosine pulse shape with 0.35 roll-off factor, 16 Mbps data rates, and 1,500 bits packet size. The results imply that a 12 dB gain can be obtained with Turbo Codes and nominal equivalent isotropically radiated power (EIRP). Similar evaluations can be conducted following the given specifications. For example, SDA optical communications terminals use on-off-keying non-return-to-zero and M-ary pulse position modulations with radio resources at 193.1 and 195.1 THz. Based on the obtained performance portfolios, uplink channel estimation can enable adaptive modulation, coding, and power control schemes based on physical-layer specifications and downlink performance. For instance, an auto-regressive moving-average model generally describes the dynamics of rain fading in Ka-bands. The transmit scheme can then vary per the fading gain to keep the SNR level while maintaining the requested power outage probability.

Satellite Swarm Hyper-Connectivity

Service and network management in the serverless platform has an end-to-end system view and can enable satellite swarms' hyper-connections to enhance global transmission capacities. To demonstrate the architectural effectiveness, we consider many stations in the ground tier as an extensive ad hoc network and characterize it with a geometric random graph. These ground stations can use Zigbee (802.15.4) technology for multihop transmissions with a 100 *kb/s* average data rate. The space tier consists of $m \times m$ satellites in a two-dimensional lattice structure, following a small-world swarm topology [11]. These LEO satellites can support Mynaric inter-satellite links with a 10 Gbps average data rate and Starlink ground-satellite transmissions with 100 Mbps. When applying the LEO swarm network in the (reinforcement learning) algorithm designs, swarm infrastructure factors should be considered together, such as the satellite connectivity over different orbits, ISL connections, and handover transitions. Accordingly, adopting the enhancements of deep learning realization via Section~\ref{sec3d} or graph modeling for LEO swarm topologies can facilitate algorithm convergence concerning different service requirements and space mission applications.

Given 1 Mb of data from a ground source station to a destination station, Fig. 3 shows the worst-case transmission delay by sole ground transmissions with long multihop routes and satellite-assisted hyper-connections with different swarm sizes. The results indicate that end-to-end delay can be reduced by at least 50% via a 2 × 2 satellite swarm's hyper-connections and up to around 90% with a larger swarm (e.g., 5 × 5). The improvement is because ground stations now can use the space tier for ultra-fast data delivery rather than conventional very-long ground routes. By adding a few satellites and tailoring their swarm structure, satellite swarm networks can resolve undependable end-to-end transmission delay and thus facilitate resilient ultra-broadband networking with SLA provisioning.

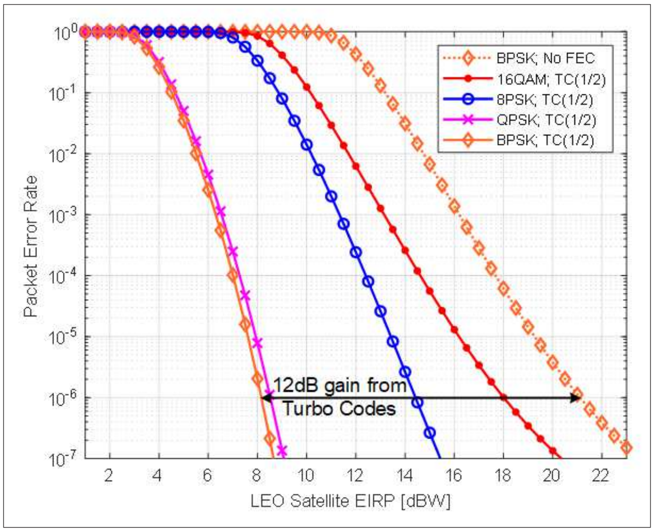

FIGURE 2. A LEO's downlink Ka-band (27.5 GHz) performance portfolios to enable adaptive ground-space communications.

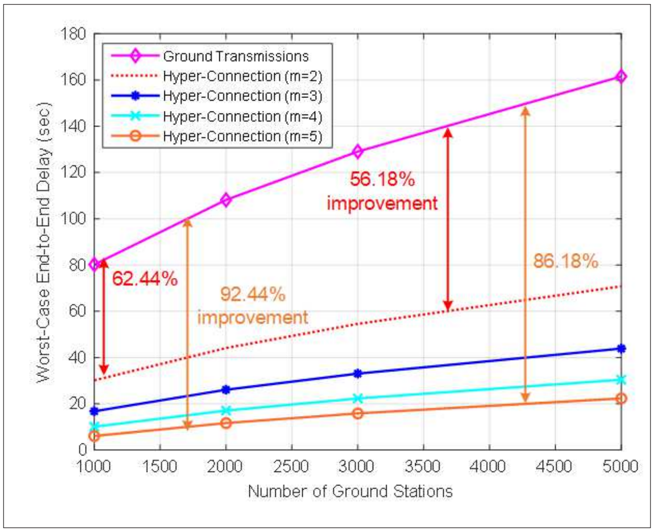

FIGURE 3. End-to-end delay of ground multihop routes versus LEO satellite hyper-connections with swarm size $m \times m$.

Multi-Agent Deep Reinforcement Learners

One primary objective of the designed serverless platform is to dynamically adjust ML workloads among heterogeneous computing units while considering their real-time capabilities. ML-SDN control engines can equip multi-agent DRL; different Table 1 deployments can be implemented to ensure effective engine coordination for superior system performance. Notably, a *multi-agent DRL* algorithm has three design components: observation processors, action predictors, and deep learners. An agent interacts with the environment (e.g., satellite swarm networks) and obtains local observations and models (e.g., current state, action, reward, and next state). An action predictor can characterize agent collaboration by predicting other agents' actions. A deep learner can derive the optimum policies based on the observation and prediction results. Furthermore, each agent/engine can upload its local parameters to the serverless platform, training neural networks with global information. Thus, our serverless edge platform can configure four learning deployments listed below for different coordination among ML-SDN control engines.

- **Individual/competitive structure:** each control engine implements its learner from its observation processor and inactivates its action predictor by considering other engines as part of the environment. Control engines can obtain rewards and new observations stored as training experiences by interacting with the entire environment. Such historical experiences can facilitate engines to carry out ML workloads with real-time capabilities.

- **Federated/collaborative structure:** control engines with larger time granularity require long periods of environment observation, which degrades model training and updating performances. Collaborative deployment can significantly reduce such processing latency, particularly for larger control cycles. Specifically, recently emerging federated learning can be applied, where each engine trains its learner and reports local parameters to the serverless platform. The platform then aggregates the collected parameters for a global model and disseminates the results to engines for their subsequent training. Also, this federated structure can quickly realize centralized training and decentralized execution of multi-agent DRL.
- **Hierarchical/leader-follower structure:** leveraging hierarchical ML-SDN infrastructures, upper/leader control engines with larger control cycles enable learners to observe and predict lower/follower actions. Then, the followers can follow the leaders' actions and environment and implement their learning. Hierarchical structures can also be extended with multiple layers to address scalability issues, e.g., leaders, sub-leaders, and followers.
- **Global/joint structure**: lastly, all control engines can upload their observations and rewards to the serverless platform for training a fully centralized learner. Then, the platform provides the results to engines to perform corresponding actions. In addition, historical experience storage and usage to enhance multi-agent DRL can be handled by only local engines, engines with the platform, or the sole platform, depending on learning deployments.

A satellite swarm can utilize beyond-line-of-sight channels and ultra-wide coverage for more robust communications with higher throughput. These MIMO LEO satellites can adopt MIMO and spread spectrum technologies to prevent active jamming attacks or harmful co-channel interference.

A compact total solution, the hardware-in-the-loop testbed, and practical experimentation are being built; the proof-of-concept results are promptly posted on our iWN lab website.

Open Research Problems

We summarize open research issues that should be investigated further to fully assess the merits of the proposed serverless satellite swarm networks.

Unsupervised Beyond-Line-of-Sight MIMO Beamforming

Two crucial challenges exist when supporting timely beamforming and high bandwidth in multi-antenna ultra-broadband satellite swarm networks. First, hybrid beamformers need low-latency beam management to provide good transmission quality in fast time-varying beyond-line-of-sight channels constantly. Such channel conditions are due to peculiar LEO satellite movement and communications band in possible all-spectral (e.g., mmWave's blockage sensitivity, THz's pronounced molecular absorption, and spreading losses). Second, supervised deep learning (i.e., conventional ML-based solutions) can address complicated beamformers with large antenna arrays (e.g., perfect channel state information via channel estimation). However, this learning technique is limited by the performance of labeling algorithms, which must label vast input data (especially in multi-user scenarios) during offline training.

Unsupervised reinforcement learning-based beamforming is one enabling technology to cope with these challenges and provide fast beam tracking for the net multi-antenna gain. In serverless edge architectures, satellite swarms can coordinate for joint operations to act as a distributed antenna system. The time-varying MIMO fading channel on space-ground communications can be modeled by extending the K-user interference channel. Average downlink data rates can be obtained via medium access control (e.g., asynchronous direct-sequence code-division multiple access). Accordingly, a user sum-rate maximization can meet the unsupervised learning need of "differentiable" objective functions. For example, one can formulate a constrained optimization to find optimal beamformer matrices and power and spectrum allocations, subject to maximum available power, spectrum constraints, and stochastic computation delay requirements.

Based on the unsupervised formulation, the remaining task is introducing computation-efficient algorithms that consistently provide good beam tracking adaptive to timely environmental changes. Deep unfolding techniques are candidates for efficient unsupervised beamformers, leveraging residual neural networks and optimization. In [12], a coarse estimator module addresses the constrained sum-rate maximization; gradient descent beamforming is then empowered with a deep unfolding module for fast convergence. Finally, unsupervised beamformers should be upgraded with reinforcement learning-enabled tracking to balance system resilience and rapid beam alignment/steering. For example, multi-agent DRL on ML-SDN control engines can use received power levels to ensure up-to-date beam tracking while satisfying computation delay requirements.

Anti-Jamming MIMO Satellite Swarms

A satellite swarm can utilize beyond-line-of-sight channels and ultra-wide coverage for more robust communications with higher throughput. These MIMO LEO satellites can adopt MIMO and spread spectrum technologies to prevent active jamming attacks or harmful co-channel interference. For example, antenna beamforming can eliminate interference by directing a null toward a jammer. In [13], a DSSS system is revamped and tested experimentally for above 100 GHz and secure spectrum sharing, ensuring coexistence between ground THz active users and THz earth exploration satellite services. More importantly, the anti-jamming capability of MIMO satellite swarms can increase to the next level by exploiting their spatial dimension with MIMO beamforming and frequency hopping spread spectrum. In particular, uplink/downlink transmissions can smartly allocate specific "virtual" rays among total available rays through swarm coordination to avoid jamming signals. Larger-scale swarm coordination can be accomplished via hardware synchronization, timing protocol designs, or the proposed serverless SDN edges. Hence, massively networked MIMO techniques can be established to assure SLAs (e.g., variable-rate MIMO links, robust and bandwidth-efficient communications) in secure satellite swarm networks.

Cyber-Harden Opportunistic Multipath Routing

For connectivity robustness and resilience, defensive and self-healing algorithms should be designed to tackle possible cyber-attacks and provide ceaseless connections in node failures, deep fades, and malicious behaviors. A straightforward solution is to create backup paths, but it is resource prohibitive to assign wireless backup capacity. Hence, one possible solution is to revamp opportunistic multipath routing algorithms to provide cyber-harden satellite swarm communications. In [14], a cognitive and opportunistic relay solution is designed for reliable communications and connections in a machine swarm. This design enables machines to cognize and adapt to environments for mitigating inter-system interference with existing networks and realizes opportunistic selections of cooperative relay machines based on link qualities. Similarly, satellite swarms can distributedly concatenate their link transmissions for end-to-end resiliency. Also, in [15], "virtual" MIMO at the session level is established, and probabilistic network-coded routing is developed for large-scale cognitive machine swarms. This work enables spatial multiplexing and diversity with session-level traffic and ensures end-to-end delay by employing network coding techniques with underlaid routing algorithms. Thus, such dynamic cooperation via multihop multipath transmissions can be exploited for the fault tolerance of satellite swarm networks, robust to a node or link failures.

Cross-Constellation Delay-Optimal Multipath TCP

Owing to serverless edge architectures, heterogeneous satellite constellations from different operators can now integrate into a hybrid space architecture through space-based adaptive communications node (SBACN) and API development for cross-constellation communications command and control. As shown in Fig. 4, a hierarchical structure can be established where an SBACN center connects to multiple SBACN terminals. These terminals integrate existing satellite operators' constellations by acting as their gateways. SBACN terminals only need to update the resource information and service requests to the SBACN center via serverless edges and enable FaaS for connectivity and SLA satisfaction without configuring or managing resources. On the other hand, the SBACN center coordinates reliable inter-constellation-level connectivity while each operator handles its intra-constellation-level management. The SBACN center hosts on-demand applications through dynamically instantiated containers and effectively computes optimal routing-path planning and resource allocation designs, avoiding underutilization while maintaining high throughput. Iteratively software upgrading efforts for the APIs and underlying algorithms are negligible.

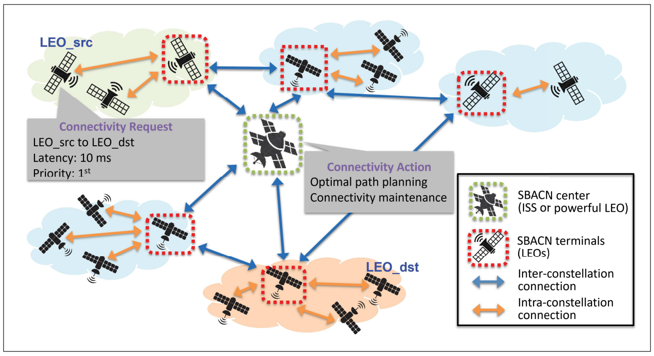

FIGURE 4. Cross-constellation SBACN swarm architecture.

Based on scalable cross-constellation architectures, a centralized delay-optimal multipath TCP (MPTCP) can be developed to minimize the end-to-end delay while eliminating frequent control message signaling from distributed algorithms. Satellite-assisted communications suffer long delays and regular ground-satellite handovers (both problematic for TCP connections). MPTCP protocols address these challenges by exploiting multiple Internet paths between a pair of hosts while presenting a single TCP connection to the upper layer. Thus, the upper-layer applications only need a single logical master TCP connection. Multiple sub-flows are then running underneath, each of which is a conventional TCP connection. Specifically, one can formulate a nonlinear optimization to find end-to-end routes with minimum average delay and no congestion concerning cross-constellation network topology and traffic to provide delay-optimal end-to-end networking. Then, fast algorithms can be exploited to give the optimal MPTCP solutions within a few milliseconds. As a result, centralized SBACN controllers implement

- Topology and traffic monitoring/prediction
- MPTCP awareness
- Multiple disjoint path discoveries, thus achieving timely and reliable cross-constellation systems.

Conclusions

Satellite swarm networks have promised to serve isolated or remote communities and fulfill the needs of landlocked areas with limited infrastructure investments. However, there is little work that simultaneously addresses satellite access and inter-tier networking within the 6G context and provides a coherent serverless architecture for such ecosystems. This article introduces unique serverless edge architectures with multi-tier deep reinforcement learners and emphasizes necessary architectural, management, and operational advances, thus bringing a new frontier for resilient access equality.

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