This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

Artificial Intelligence for Satellite Communication: A Survey

Gianluca Fontanesi, Member, IEEE, Flor Ortíz, Member, IEEE, Eva Lagunas, Senior Member, IEEE, Luis Manuel Garcés-Socarrás, Member, IEEE, Victor Monzon Baeza, Senior Member, IEEE, Miguel Ángel Vázquez, Member, IEEE, Juan Andrés Vásquez-Peralvo, Member, IEEE, Mario Minardi, Student Member, IEEE, Ha Nguyen Vu, Senior Member, IEEE, Puneeth Jubba Honnaiah, Clement Lacoste, Student Member, IEEE, Youssouf Drif, Member, IEEE, Liz Martinez Marrero, Student Member, IEEE, Saed Daoud, Member, IEEE, Tedros Salih Abdu, Member, IEEE, Geoffrey Eappen, Member, IEEE, Junaid ur Rehman, Wallace Alves Martins Senior Member, IEEE, Pol Henarejos, Member, IEEE, Hayder Al-Hraishawi Senior Member, IEEE, Juan Carlos Merlano Duncan, Senior Member, IEEE, Thang X. Vu, Senior Member, IEEE and Symeon Chatzinotas, Fellow, IEEE

Abstract—This paper provides a comprehensive survey on the application and development of Artificial Intelligence (AI) and Machine Learning (ML) in satellite communication (SATCOM). It explores the increasing integration of AI/ML technologies in SATCOM systems, highlighting their potential to enhance performance, efficiency, and adaptability in response to growing demands for connectivity and data processing. The survey categorizes various use cases across different layers of satellite networks, detailing conventional solutions and the advantages of employing AI/ML techniques. It discusses the challenges associated with onboard processing, including hardware constraints, radiation tolerance, and the need for efficient resource management. Furthermore, the document examines the role of neuromorphic computing and COTS (Commercial Off-The-Shelf) devices in facilitating AI applications in space environments. Finally, we discuss the long-term developments of AI in the SATCOM sector and potential research directions. Overall, the survey emphasizes the transformative impact of AI/ML on the future of SATCOM, paving the way for innovative solutions in next-generation satellite networks.

Index Terms—Satellite Communication, Machine Learning, Artificial Intelligence, Non-terrestrial Networks

Manuscript received XXX, XX, 2021; revised XXX, XX, 2021.

The authors from University of Luxembourg have been supported by the Luxembourg National Research Fund (FNR) under the project SmartSpace (C21/IS/16193290). In addition, this research was funded in part by the European Union's HORIZON.1.2 - Marie Skłodowska-Curie Actions (MSCA) programme under grant agreement ID 101131481 and the Luxembourg National Research Fund (FNR), grant reference DEFENCE22/IS/17812162. The authors from CTTC have been supported by the project SOFIA PID2023-147305OB-C32 funded by MICIU/AEI/10.13039/501100011033 and by FEDER/UE and by the Catalan government through the project SGR-Cat 2021-01207.

G. Fontanesi was with the Interdisciplinary Centre for Security, Reliability, and Trust (SnT), Luxembourg, L-1855 Luxembourg at the time the manuscript was submitted, and now with Radio Systems Research, Nokia Bell Labs, Stuttgart, Germany.

F. Ortíz, E. Lagunas, L. M. Garcés-Socarrás, V. Monzon Baeza, J. A. Vásquez-Peralvo, M. Minardi, H. N. Vu, P. J. Honnaiah, C. Lacoste, Y. Drif, T. S. Abdu, G. Eappen, W. A. Martins, J. C. Merlano Duncan and T. X. Vu are with the Interdisciplinary Centre for Security, Reliability, and Trust (SnT), Luxembourg, L-1855 Luxembourg

Symeon Chatzinotas is with University of Luxembourg, 1855 Luxembourg City, Luxembourg and with College of Electronics & Information, Kyung Hee University, Yongin-si, 17104, Korea

J. ur Rehman is with the Department of Electrical Engineering and the Center for Intelligent Secure Systems, King Fahd University of Petroleum and Minerals, Dhahran, 31261, Saudi Arabia

Hayder Al-Hraishawi is with the Department of Electrical Engineering, University of South Florida, Tampa, FL 33620 USA.

M. Á. Vázquez and P. Henarejos are with the Centre Tecnologic de les Telecommunicacions de Catalunya.

(Corresponding author: Gianluca Fontanesi, gianluca.fontanesi@nokia.com)

I. Introduction

Satellite communication (SATCOM) and Non-terrestrial networks (NTNs) are seeing unbounded growth, offering a new world of enthralling possibilities for global coverage, connectivity, and scalability. Space-based communication systems have been typically used to cover vast airspace and sea areas, supplementing existing terrestrial networks for global connectivity. With the increasing demand for broadband connectivity, non-terrestrial operators are investing in new orbits and new constellation designs to provide a cost-efficient response to such a market. In addition, NTNs technology has been identified as a key component of the upcoming 5G and beyond cellular communication, particularly for backhaul services, backup connectivity, and extending coverage in remote or isolated regions of the globe [1].

While the term NTNs includes a huge variety of space-borne and aerial communication networks, such as Geo-Stationary Orbit (GEO), Medium Earth Orbit (MEO), Low Earth Orbit (LEO) satellite constellations, High Altitude Platforms (HAPs) systems, Low Altitude Platforms (LAPs) systems, and Air to Ground (A2G) networks, for the sake of space and clarity, this survey has focused on satellite communications systems limited to GEO, MEO, LEO.

A. Need for AI/ML in SATCOM

The SATCOM ecosystem is currently experiencing a revolution in advanced technological solutions and raising a new space era where lower orbits are emerging as a low-latency alternative to conventional GEO communication systems. The time and geographical dependency of user demands combined with the dynamic movement of low-orbiting satellites have resulted in new antenna architectures with beamforming capabilities and reconfigurable payloads with the capability to adapt the payload configuration in response to traffic needs.

This new communication era brings fundamental operational challenges. Most deployed SATCOM systems largely depend on human expertise, and manual intervention [2]. This has two main drawbacks. First, human involvement in system control activity leads to high Operational Expenditure (OPEX) and latency [3]. Second, the rapidly changing radio environment of the new space scenarios claims for autonomously adaptive mechanisms that human intervention cannot offer. Lastly, the multitude of use cases and scenarios served by SATCOM in the following years will produce data in large quantities. Thus, it is beneficial and necessary to make satellites capable of automatically generating reliable actions using the data produced.

Artificial Intelligence (AI) is entering SATCOM with the great promise to solve the abovementioned challenges. Intelligent systems enable automation to process specific input from satellite data and translate them into actions. In addition, data-driven techniques might substantially reduce the OPEX.

Given the significant momentum and recent activities promoting AI in SATCOM, it is timely to survey this brand-new field.

Certain literature agrees to classify machine learning (ML) as a branch of AI, whose goal is to allow computers to learn from data. In some way, ML is just one way to achieve AI. However, most of the time, both terms are used interchangeably, such as the idea of a machine mimicking human intelligence. Therefore, in Section II, we address this dilemma for a better understanding of the reader.

B. Related Surveys and Contribution

ML has appeared as a promising alternative for dealing with computationally expensive optimization procedures. For this reason, and with the exponential increase in the number of datasets available, ML has become a fundamental technology in different areas of wireless communications [4]. In this context, ML has proven to be an exciting tool for accelerating complex optimization procedures for general wireless communications [5]. Many surveys cover the development of ML models to support wireless networks.

About the direct application of ML models in SATCOM, there are only a handful of survey papers summarising it. For this reason, in the following subsections, we will present the surveys describing SATCOM and the application of AI.

Due to the increasing importance and interest in SATCOM, several works survey different aspects of SATCOM. The work in [6] deals with the vision of SATCOM in conjunction with Unmanned Aerial Vehicles (UAVs) and terrestrial networks to provide a feasible and cost-effective solution for continuous and ubiquitous wireless coverage. The innovation and transformation phase experienced by SATCOM, driven by on-board processing capabilities, NTNs and space-based data collection/processing, is explained in [7]. The algorithms and applications of Earth Observation (EO) are covered in [8]. Cubesats are a special class of miniaturized satellites commonly used as teaching tools, and technology demonstration [9]. The work in [10] describes all the potential future applications of Cubesats for SATCOM.

Other papers survey a variery of SATCOM aspects, such as handover schemes [11], non Geostationary satellite systems [12], syncronization techniques [13], MIMO techniques [14].

The important case of SATCOM as Internet of Things (IoT) enabler is treated in several surveys [7], [15], [16]. The works [7], [15] categorize the use cases in which satellites serve IoT devices used in global transportation and agriculture applications. In local-area services, a satellite serves a specific set of IoT devices in applications such as smart grid systems.

Unlike previous works, in this survey, we embark on an exploration of the multifaceted applications of ML in SATCOM. Our aim is to provide a comprehensive survey of the developments in this dynamic field, drawing on a wide range of studies. While not intended as a tutorial or survey papers, some related works focus only on mega satellite network communications [17] or SATCOM operations which are strongly dependent on human intervention [2]. Other works address deep learning (DL) only [18], [19] or AI for space missions [20]. The work in [19] is focused on the evaluation of different image compression techniques applied to satellite data. Furthermore, [21] covers a limited number of use cases and challenges and is focused only on covert SATCOM.

The use cases presented in [22] represent only a small part of the use cases presented in this manuscript, as highlighted in Table II. In addition, this survey provides an evaluation of several ML techniques through different case studies (such as beamforming, user scheduling and RRM). The evaluations are based on the publications of our research group and provide the reader with valuable insights and key findings. Finally, unlike [22], we also review SATCOM-oriented hardware and chipsets, including neuromorphic processors. For the presented AI chipsets available for SATCOM, we provide an indication of the main features, computing power, suitability for on-board applications and possible use cases.

A detailed survey of this type was still missing, and it is of great importance to look at the appealing AI/ML approaches for SATCOM with an implementation perspective. By directing attention to these sources, our survey aims to serve as both an informative overview and a gateway to more specialized knowledge, enabling readers to delve further into areas of specific interest within ML applications in SATCOM.

The contributions of this paper can be summarized as follows:

- We present an extensive classification of the most

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

important use cases in SATCOM, and we group them based on an OSI-oriented architecture.
- We describe each presented use case, the main related challenges, and the conventional tools to address them. We further present the main ML techniques applied to each use case, and we classify them by whether the training is onboard or on the ground. In this section, we provide valuable insights and key takeaways for leveraging various AI techniques in the context of SATCOM.
- We assess the hardware landscape for current and next-generation processors for onboard SATCOM, presenting an extensive review of commercial AI chipsets and giving some insights on what hardware devices can be used for a particular use-case. We introduce the main limits and constraints of the AI/ML for SATCOM onboard operations and we indicate the most recent attempts to deploy ML SATCOM use cases proof-of-concepts.
- We analyze the main challenges for the SATCOM from the perspective of future network deployment. We also present novel and futuristic trends.

This paper consists of six main sections. Specifically, we first briefly introduce the main AI/ML learning frameworks. Our survey does not describe how various ML methods operate. There are numerous books and research papers on this topic; we refer the reader to papers such as [23], [24], for a detailed (although still wireless networking-related) discussion of these methods. We then discuss in Section III the role of AI in SATCOM, highlighting the main differences between an onboard or on-ground implementation. Section IV presents an extensive list of use cases in SATCOM and NTN. For each use case, we show the benefits of using ML-based techniques. Section V presents an analysis of the HW solutions for AI/ML implementations for SATCOM. Last, Section VI on the challenges and future directions of SATCOM and NTNs concludes the paper.

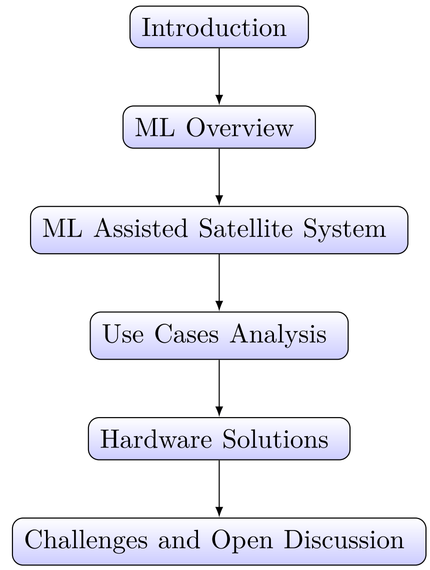


Fig. 1: Structure of the paper

II. Machine Learning Overview

A. Artificial Intelligence, Machine Learning and Deep Learning

AI attempts to understand the essence of intelligence and simulate the processing of information by machines in the human brain. ML, a branch of AI, is related to computational statistics and predictions by exploiting the experience and knowledge gained from the data [28]. ML involves learning from data and making decisions or predictions. Essentially, it is based on the assumption that machines can have intelligence that allows them to learn from previous computations and adapt to the environment.

The available ML models in the literature can be classified into classification, regression, and structured learning models [29]. A classification model is used to solve binary or multiple classification problems and a regression model can be used to make predictions. The structured learning model is widely used in many fields, such as natural language processing. Moreover, ML can also be classified from the training method into supervised, unsupervised, and Reinforcement Learning (RL) [29].

DL is essentially a branch of ML, which allows a model to make classifications, predictions, or decisions based on large data sets, without being explicitly programmed. Unlike conventional ML algorithms based on predefined features, DL can extract essential features from the raw data through multiple layers of nonlinear processing units to make predictions or perform target-based actions. DL's main advantages are to extract features automatically. The best known DL models are neural networks with a sufficient number of hidden layers. Even though the multilayer neural network (NN) was proposed several decades ago, unprecedented interest has only recently arisen due to the advancement of backpropagation-based training as well as the success of GPU. deep neural networks (DNNs) aims to approximate any complex function by a composition of simple operations on neurons. DNNs can automatically extract essential features from complex structure input data. No human-designed learning process is needed, significantly reducing the effort in elaborating features. DL may learn meaningful patterns from unlabeled data in an unsupervised manner. A key challenge of employing DL in mobile communication systems lies in designing optimal DNNs for different scenarios just so that the model can be effectively trained in the offline stage and achieve good performance in the online testing stage. Representative typical DL models include multilayer perceptron (MLP), deep belief network (DBN), autoencoders, convolutional neural network (CNN), Recurrent Neural Network (RNN), and generative adversarial network (GAN) [30]–[32].

Furthermore, ML learning approaches for wireless communication can be grouped into supervised learning, unsupervised learning, semisupervised learning, and RL

TABLE I: Relevant surveys and tutorials on artificial intelligence (AI)/machine learning (ML) and/or satellite communications.

Network	Source	Main Scope	ML Focused	AI HW	Use Cases	Open Issues	ML Eval
SATCOM	[1], [6], [25]	Survey NTNs	No	No	No	Yes	No
	[7], [26]	Next Generation SATCOM	No	No	Yes	Yes	No
	[8]	Earth Observation	No	No	No	No	No
	[10]	Cubesat Applications	No	No	No	No	No
	[11]	Handover schemes	No	No	No	No	No
	[12]	non-GEO satellite comm.	No	No	No	No	No
	[13]	Distributed Satellite Systems	No	No	No	No	No
	[14]	MIMO Techniques for Satellite	No	No	No	No	No
	[15]	Satellite Comm in Internet of Things	No	No	No	No	No
	[16]	Satellite Internet of Things	No	No	No	No	No
	[20]	Space mission	Yes	No	No	No	No
ML & SATCOM	[22]	ML techniques for SATCOM	Yes	No	Yes	No	No
	[21]	covert SATCOM	Yes	No	No	No	No
	[2]	ML for SATCOM operation centers	Yes	No	Yes	No	No
	[17]	Survey on AI for Mega Constellation	Yes	No	Yes	No	No
	[18]	Deep Learning in Space	Yes	No	No	No	No
	[19]	Deep Learning in Space	Yes	No	No	No	No
	[27]	ML for Radio Resource Management	Yes	No	No	No	Yes
	This work	AI for SATCOM	Yes	Yes	Yes	Yes	Yes

TABLE II: Overview of the use cases presented in related works and contribution of this manuscript

Use Case	Paper describing it	Contribution of this paper
Antenna Beamforming	Only this Paper	Review of related works, Evaluation
Resource Allocation	[22] (frequency), [2] (frequency, power)	Frequency, power, beam, bandwith, Evaluation
Link adaptation	Only this paper	Review of related works
Spectrum Sensing and Classification	[17], only LEO	Inclusion of more related works
Interference Management	[22], [2]	Inclusion of more related works
Intersatellite Synchronization	Only this Paper	Review of related works
Precoding	Only this Paper	Review of related works
Link Quality	[17], only LEO	Inclusion of more related works
Coding	Only this Paper	Review of related works
User Scheduling	Only this Paper	Review of related works, Evaluation
NOMA Access	Only this Paper	Review of related works
Rate Splitting	Only this Paper	Review of related works
Constellation Routing	Only this Paper	Review of related works
IoT Channel Access	Only this Paper	Review of related works
Traffic Prediction	[22], [2] up to 2020	Inclusion of more related works
Integrated Satellite-terrestrial	[22]	Inclusion of more related works
Edge Computing	Only this Paper	Review of related works
Device Authentication	Only this Paper	Review of related works
Quantum Key Distribution	Only this Paper	Review of related works

[30].

- Supervised Learning: uses labeled input and output data to train a model and make predictions on new data. Examples include Naive Bayes, KNN, random forest, NN, SVM, and DT. Examples of use cases include radio resource management [33], traffic prediction [34] and beamforming [35].
- Unsupervised Learning: uses unlabeled data to cluster and aggregate information. Examples include K-mean, SOM, HMM, and RBM. Use cases include user-scheduling [36] and anomaly detection [37].
- Semi-supervised Learning: a combination of supervised and unsupervised learning that uses both labeled and unlabeled data to improve the model's performance. Examples include descriptive pseudo labeling, which generates pseudo-labels for the unlabeled data, and algorithms that require certain assumptions about the data, such as manifold, low-density, clustering, and smoothness assumptions.
- Reinforcement Learning: learns by trial and error to explore the best actions during a dynamic process. RL can be model-based or model-free, and it does not require an accurate mathematical model of the environment. Use cases include user scheduling, spectrum sharing [38], or link adaptation [39].

While a tutorial on how to create a dataset and divide it between training and testing is outside the scope of this paper, we highlight that there are difference phases of ML techniques for assisting SATCOM at any stage of network communication: training, testing and inference [27]. First, the ML model undergoes the training phase. The goal is to find the optimal model parameters to assist the SATCOM task for the system conditions. In a separate testing phase the model's performance is evaluated on unseen data, called the test dataset, which was not used during the training process. In contrast, during the inpherence phase the trained model is used to make predictions or decisions on new, unseen data in a real-world scenario. In this phase, the model takes input data and produces output predictions or classifications without any further training. However, the ML framework encompasses a broader spectrum of learning processes, not limited to the previous mentioned phases. In RL applied to SATCOM, the model learns and evolves its strategy through a series of trials and feedback, constantly adjusting to new conditions. The goal here shifts from finding optimal pre-trained model parameters to enabling the system to make informed decisions dynamically based on real-time learning. Such an approach is particularly pertinent in SATCOM, where changing environmental factors and system conditions necessitate a more adaptive and responsive ML strategy.

III. Machine learning assisted satellite system

A. Introduction

The satellite communications world is progressing towards having all the ingredients making ML suitable for particular satellite-related use-cases. In response to the increasing telecommunication's market demand for flexibility, satellite payloads are being digitalized. Full digital payloads are paving the way for satellites with a higher level of flexibility to efficiently support peaks in demand.

These payloads include capabilities like onboard channelization, interference mitigation techniques, digital beamforming and/or time flexibility. Beside the flexibility of next generation satellite systems, satellite payloads come with challenges that the application of ML techniques can help to solve:

- Satellite payloads are known by their nonlinear effects and general impairments introduced by hardware components. Although different models for such impairments exist, such models may not accurately present the actual signal. To deal with such a complex end-to-end system model, ML, as in the form of neuromorphic computing, can be used either to predict it directly from experience, such as events of power interruptions [40]. Bioinspired Neuromorphic processors (NPs) are a promising alternative to work as efficient coprocessors in ML applications where temporal signals are involved and/or require continuous adaptation in SATCOM systems. Unlike conventional processors that operate in batch mode, that is, collecting many samples before processing them, NPs can process in streaming mode. Due to their energy efficiency and continuous on-board adaptability, NPs represent an excellent opportunity to open up the potential benefits of AI solutions for SATCOM systems. Moreover, NP implementation can take advantage of non-volatile memory devices based on technologies beyond CMOS [41].
- Automatic dynamic resource allocation algorithms are a key innovation to make satellite operators allocate bandwith dynamically to designated areas and save resources. To unveil the full potential of such new added flexibility, NN [33], [42] and RL [43] can help accelerate the complex optimization procedures for beam hopping, power and bandwidth allocation. Furthermore, CNN and Long Short-term Memory (LSTM) are known to be a great tool for network traffic prediction [44], which is also a key aspect when deciding on when and how to reconfigure the satellite payload.
- The ground segment is evolving towards a multi gateways (GWs) environment. In the case of GEO, this is because the congestion of the Ka band is pushing feeder links to operate in higher bands, e.g. Q/V bands. In the case of NGSO, the need of multi-GW is dictated by the movement of the satellites and the need to have often a connection to Earth for the uplink / downlink of the signals. The multi-GW environment resembles the promising Cloud Radio Access Networks (C-RAN) architecture of cellular systems [45], where the control plane is logically centralized gathering the whole system intelligence providing a global view of the entire system status and enabling cross-layer system-wide optimization. In this context, DL-based automation (e.g. DL [46]) applied at the central node could autonomously allows to develop a more efficient switching-mechanism between GWs while reducing the critical processing time for decision-making. The benefit for operators is the availability of very large data sets from their networks and the possibility to apply a range of data processing, geo-spatial, ML and other tools to manipulate and analyse such data, with the main goal to optimize the system operation.
- The emergence of piggy-back launches, nano and microsat technology and new higher-risk accepting development approaches and the availability of venture capital, new innovative mission concepts have been envisaged and implemented. The trend of having space-based mesh network of small satellites opens up a plethora of opportunities for massive self-organized, reconfigurable and resilient NGSO satellite constellations, which can operate as a global network instead of a single relay. To exploit NGSO satellite signals, frequency and time misalignment caused by the fast system mobility shall be compensated. For this, accurate estimation and prediction of ephemeris is a key aspect and has been the subject of research using NN, e.g. [47]. In addition, the highly dynamic and overlapped coverage areas on ground, result of the distributed nature of NGSO constellations, brings many operation challenges, e.g. the dynamic handover of users from satellite to satellite, the edge-processing in space, the cooperative transmission from multiple satellites, that researchers are trying to tackle via ML, as DNN and RL [48], [49].

Each of those relatively new challenges can have po-

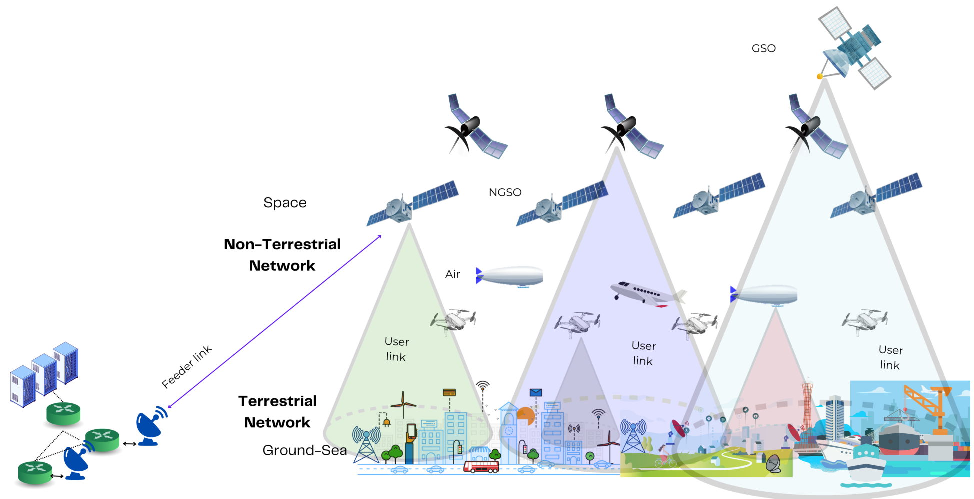


Fig. 2: Communications Architecture

tential benefits on the application of ML, as we will see in the next parts of this paper. Before that, we present in the following an overview of the conventional satellite architecture and how ML can be integrated into such systems.

B. Communications Architecture

Satellite network architecture comprises space, ground, control, management, and user segments, as shown in Figure 2. (i) Space segment comprises the satellites organized in the constellation. It supports routing, adaptive access control, and spot beam management. (ii) The ground segment consists of satellite gateways (GWs) interconnected by optical backbones and satellite terminals (STs) that provide connections for end-user devices. The GWs and STs are interconnected through the space segment. (iii) The control and management segment consists of the network operations centers (NOCs) of the ground segment and the payload operations centers (SOCs) of the space segment. The NOCs and SOCs provide real-time management and control functions for the satellite networks. They perform connection establishment, tracking and release, admission control, resource allocation, satellite network element configuration, security, fault, and performance management. Co-located GWs, NOCs, and SOCs are commonly referred to as satellite hubs. (iv) The user segment comprises all end-user devices used by end-users to consume satellite-based services, fixed or mobile. They access satellite networks directly or through terrestrial access points [50].

C. On-ground or Onboard ML training in SatCom

The main point of debate in the deployment of ML for satellite communications revolves around where to deploy the ML system. Online Training, in a broader sense, refers to any form of ML training that occurs in an ongoing manner as new data become available. This can happen on a device (like onboard training) but can also occur on a server or cloud infrastructure that continuously updates the model as new data streams in. Conversely, offline learning, characterized by its reliance on a static dataset, minimizes processing delays during the inference phase, offering a more streamlined approach. However, it demands a comprehensive database for training and might falter in unforeseen scenarios due to its static nature.

This dilemma is closely related to the decision to conduct training online or offline, which adds another layer of complexity to the ML deployment process. In the context of satellite technology or similar fields, ”online training” and ”onboard training” can sometimes be used interchangeably, but they are not inherently the same in all contexts. The use of terms online/offline and on-ground/on-board for ML in SATCOM can be found in several manuscripts of the last years, as [3], [51]–[55], presented in main NASA/ESA or main SATCOM journals or conferences. Onboard training specifically refers to training a ML model directly on the device or platform itself (e.g., a satellite, a drone, or an autonomous vehicle). This implies that the training process occurs where the data is being collected and is processed by the onboard systems, which can be crucial for applications needing real-time decision-making and where communication delays to a central server are a concern. The onboard configuration suggests a dynamic approach where the ML model is trained and updated directly on the satellite. This allows instantaneous system adjustments without terrestrial communication delays, but at the cost of increased demand processing and power requirements. Online-trained ML models can make decisions locally without relying heavily on ground station intervention, reducing the need for constant human supervision. Online ML training also provides flexibility to adapt to unforeseen changes. Sat-

TABLE III: Benefits and Challenges for an Online or Offline ML training in SatCom

ML Training in SatCom	Benefits	Challenges
Onground	Lower Latency Improved Autonomy Flexibility to adapt to unforeseen changes Higher Privacy	Limited Computing Capacity on-board Longer Processing Time Limited Power Radiation Tolerance
On-ground	Reduced processing time Large computational resources	Not flexible to sudden network' changes Inaccurate in unexpected situations Higher Latency

Com environments can be dynamic and new patterns, or anomalies, may emerge that were not present during initial training. However, limited satellite computing resources make it challenging to train complex ML models directly on the satellite. Restricted computing power can limit the complexity of the model, affecting its learning capabilities and overall performance. The new introduced ML chips to target onboard deployment are reviewed in Section V.

On-ground strategy involves ground-based model training and inference on powerful land-based computational resources, with decisions communicated to the satellite. This method simplifies model management and reduces satellite load but may encounter delays due to the communication gap between earth and space.

For ease of explanation, in this manuscript, we refer to onboard training as the online training of an ML model directly on the device during operation, while on-ground refers to an offline method. Note that hybrid models are still possible, aiming to exploit their respective advantages while minimising their limitations. For example, an on-ground-online architecture uses continuous data input for real-time model training on the ground, with updated decisions being sent to the satellite in real time. Table III summarizes the benefits and challenges of the two approaches mentioned above.

D. On the robustness of ML in SATCOM

The degree to which an ML agent accomplishes a real-world task can be examined from two perspectives: performance and robustness. These two properties represent two distinct goals. It should be noted that performance and robustness are not necessarily independent, as an ML agent that performs poorly is unlikely to be robust. However, the opposite may not hold true. Robustness in ML can generally be challenged by several factors, including learning from limited samples, dealing with delays in the system, high-dimensional state and action spaces, safety constraints that hinder exploration, partially observable environments, and real-time inference [56].

First, the robustness of ML algorithms applied to SATCOM can be challenging due to the real-time inference of deep reinforcement learning (DRL) algorithms. Real-time reward and action with the environment can be considered risky in SATCOM, as it can not only consume valuable satellite resources, but also cause irreversible damage to satellite equipment due to some operational errors. To overcome this problem, the authors in [57] propose an approach to learn and optimise task offload decisions by using the stored historical decision data and specifically applying the Soft Actor Critic (SAC) algorithm. This approach avoids relying on real-time interactions with the environment. Another approach to enabling agents to learn from offline logs or external policies, rather than directly interact with the environment, which may be costly or impossible, is represented by offlineDRL [58] and Model-based RL [59]. In this proposed scheme, the model-free random access DRL algorithm is developed using simulated experience without risky interactions with the environment.

Since safety is critical for space applications, owing to the high cost of failure, more predictable approaches to AI could be preferred. The impossibility of de facto testing the set of weights resulting from training, performed on a finite number of data, for all possible inputs might be considered another reason of risk [51]. This aspect is a real concern for the usability of models trained before the launch of satellites, whose training is not performed on the original satellite data. However, this problem is mitigated by the possibility of reconfiguring the models during the mission, made possible by the use of modern COTS ASICs, and by the reduction in the size of the files needed to program them, which is becoming compatible with the uplink bandwidth of small satellites. As concrete examples on the performance of this approach in SATCOM, the work in [55] shows a successfully attempt to run an AI CNN directly inferencing on a dedicated accelerator onboard a satellite. A recent ESA study [60] investigated different distributed scenarios with key goal of rapid response. The authors move the training of a pre-trained segmentation model directly onboard Unibap iX10-100 satellite hardware, and perform the finetuning as soon as data are acquired. Through a simulation software, onboard and operational constraints, including thermal, power, bandwidth and communication constraints are constantly monitored. The results show improvements in segmentation performance with minimal training data and fast fine-tuning when satellites frequently communicate model updates. This followed a 2023 work [61] that demonstrated an instance of training a DL model onboard Earth Observation satellite hardware, highlighting the advantages of deploying pre-trained models onboard.

On the one hand, SATCOM already induces a large propagation delay due to the long transmission distance, and specific ML-related operations (e.g. fine-tuning, delayed reward) may add additional delay. The promising results of [55], [60], [61] show the robustness of ML

TABLE IV: Robustness and Delay Handling of ML in SATCOM

Challenge	Method to Overcome	Reference	
Safe Training	Offline-DRL	[57]–[59]	
Safe training	Fast Fine tuning	[60], [61]	
Delay	Delay-aware MDP	[62], [63]	
Delay	Offloading Techniques	[64], [65]	

in SATCOM against the intrinsic system large delay of SATCOM and ML fine-tuning operations.

DRL experimental setup generally assumes negligible delay when operating, observing new states or receiving rewards. That might not be the case in the real world. Specifically, in SATCOM, delay can be caused due to the satellite link. Different solutions can be found in the literature that can be investigated in SATCOM and mitigate the risk of wrong decisions. Those solutions range from including artificial delays in the training process to simulate the real world scenario [66], to the delay-aware Markov Decision Processs (MDPs) framework [67] to account for delayed dynamics. Some applications of the mentioned techniques can already be found in SATCOM. A delay-aware MDPs is proposed in [62]. A system delay RL based on Delay MDP is proposed in LEO satellite integrated networks to overcome delay in network latency and computational bottlenecks and prevent the DRL agent from operating with outdated information.

On the other hand, due to the large space-ground propagation delays, some information might not be up-to-date. To overcome otdated estimated channel state information (CSI), the work in [63] utilizes a Deep Deterministic Policy Gradient (DDPG) algorithm to handle the continuous action space, and employ state augmentation techniques to deal with delayed observations and rewards. The results show that the DRL agent is capable of exploiting the time-domain correlations of the channels to construct accurate TPC matrices. This is because the proposed method is capable of compensating for the effects of delayed CSI in different frequency bands. In addition, the outdated delayed CSI is overcome in [68] making use of channel prediction via Echo state network (ESN) model. Finally, [65] introduces clustering and a decentralized multi-agent DRL to speed up beam hopping and perform the resource allocation on demand, decompiling the resource allocation into every cluster.

E. Ongoing Activities

Table V provides an overview of the most relevant activities carried out by private and public institutions worldwide on the development of ML in SATCOM, focusing on the most advanced level of technological readiness. Each project is briefly introduced below, also mentioning the target use case.

Late 2020, SPIRE company, within ESA's Earth Observation Science for Society Programme, launched the so-called Brain in Space project. Based on SPIRE's LEMUR 3U platform, Brain in Space provides an on-the-ground simulated testbed including multiple new embedded ML modules for users to schedule, upload and test their ML-powered applications.

1) ESA: The European Space Agency (ESA) opened an AI-related call for SATCOM for the first time in 2019 to investigate the applicability of AI techniques in satellite communications. Several potential use cases were shortlisted during these projects. A preliminary evaluation of a small number of them was carried out to provide guidelines for future research; (i) SATAI - Machine Learning and Artificial Intelligence for Satellite Communications and (ii) MLSAT - Machine Learning and Artificial Intelligence for Satellite Communication. In the first three different proof-of-concepts are developed for automatic interference detection, flexible paylod and traffic prediction.

In 2020 ESA pioneered the deployment of ML into space for earth observation onboard a 6U Cubesat called Φ-Sat-1 using an Intel Movidius chip [70], with the intent of demonstrating and validating the state-of-the-art DL technology applied in-orbit for autonomously processing Earth Observation data.

ESA funded the 'MLSAT - Machine Learning and Artificial Intelligence for Satellite Communication' in 2020 [71], which investigated and evaluated the precoding matrix computation of GEO satellites using a two-step procedure with autoencoders. In 2023, ESA launched a new activity called Sixth Generation (6G) Satellite Precursor, which aims to develop an in-orbit laboratory. This will allow the R&D process to be implemented early in the 6G rollout, so that the satellite industry can adapt its technologies, products and use cases to work alongside terrestrial communications infrastructure. An AI chipset will be considered as part of the in-orbit laboratory.

2) NASA: NASA has been actively exploring the Cognitive Radio (CR) framework for satellite communications within the John H. Glenn Research Center's radio testbed aboard the International Space Station. In addition, a custom edge computing solution for DNA sequencing on the International space station (ISS) on HPE's Spaceborne Computer-2 eliminates the need to move the massive data generated by the DNA sequencing project on the ISS by presenting containerised analysis code where the data is generated [72]. Leveraging the local computing power available on the ISS reduces the dependency on Earth and the time it takes to get results. The customised solution uses Red Hat CodeReady Containers, a single-node OpenShift cluster. This solution connects back to the IBM Cloud on the ground, where researchers will develop, test and get their code ready for deployment to the ISS. A ground-based solution on IBM Cloud will allow users to submit jobs over a VPN connection to HPE ground systems, which will securely communicate with HPE Spaceborne Computer-2 systems on the ISS, where Red Hat CodeReady Containers are installed. This solution will not only help accelerate research on the ISS, but also open the door to many new explorations on the ISS and future space missions.

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

TABLE V: Ongoing Activities

	Project Name	Object	Ref	Use Case	ML type	Status
	SDN-based testbed	routing Beyond 5G NTN	[69]	Constellation routing	routing	Completed
ESA	SATAI	ML and AI for SATCOM		interference detect., flexible paylod, traffic prediction	deep learning	Completed
	Φ-Sat-1	ML and AI for SATCOM	[55], [70]	classification, prediction	CNN	Completed
	6G Satellite Precursor	develop an in-orbit laboratory		spectrum allocation	DNN	Ongoing
	MLSAT	proof-of-concept (PoC)	[71]	precoding	autoencoder,regression forest	Completed
NASA	NASA ISS x IBM Space tech	edge computation in space	[72]	caching	edge computing	Completed
European Commission	Stream B	ML-powered optimizations for the integrated 6G and NTN	[73]		FL RL	Ongoing
	ATRIA	ML for SATCOM systems	[74]	flexible payload, beamforming	CNN	Ongoing
	DYNASAT	ML for SATCOM systems	[75]	User scheduling, beamforming	clustering	Completed

3) European Commission: The Smart Networks and Services Joint Undertaking (SNS JU) recently awarded the first batch of projects to facilitate and develop industrial leadership in Europe in 6G networks and services [73]. Among the awarded projects, some of them included ML-powered optimizations for the integrated 6G and NTN. The goal of such activities is to improve performance and automation, achieve zero-touch network management and timely monitor and predict overall network behaviour.

On the other hand, the European Union's Horizon 2020 research and innovation programme already granted a few space-related projects, e.g. ATRIA [74] or DYNASAT [75], both including the investigation of ML for SATCOM systems. A general performance enhancement is the goal of these projectd, with focus on several use case, from flexible beamforming, user scheduling, precoding to beamforming.

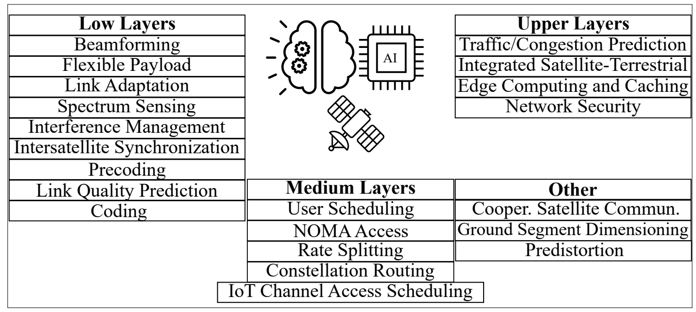


Fig. 3: Classification OSI-oriented for the use cases presented in Section IV

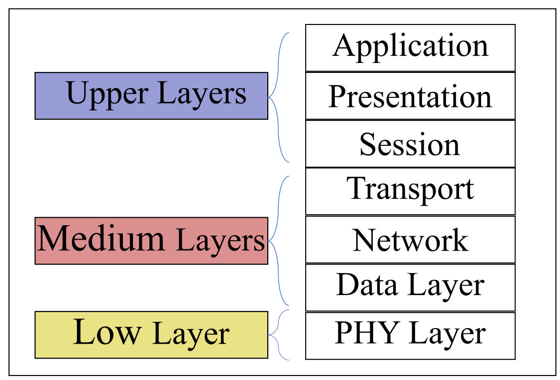


Fig. 4: Classification of OSI layers among Low, Medium and Upper

IV. Use Cases Analysis

This section presents in detail the main SATCOM use cases. We have divided the used cases in three layers, that group the conventional OSI layers (Fig. 4). For each use case we present (i) Motivation and Description, (ii) Conventional solutions and (iii) ML solutions. Our goal is to present a comprehensive overview of the current state of research in this dynamic field, drawing from a wide array of studies. For readers seeking in-depth understanding and specific details on the design considerations and motivations behind the selection of ML models for particular use cases, we encourage a closer examination of the individual studies cited in our survey. By directing attention to these sources, our survey aims to serve as both an informative overview and a gateway to more specialized knowledge, enabling readers to delve further into areas of specific interest within ML applications in SATCOM. Referenced articles are categorized and summarized in table XIII. Note that NN approaches have a dedicated column to include literature that do not refer to supervised learning.

A. Low Layers

1) Antenna Beamforming:

a) Motivation and Description: An antenna array consists of multiple same-characteristic antennas separated by a specific distance, determined by the lattice, which can be square, triangular or irregular. The radiation pattern maxima, beamwidth, side lobe level (SLL), and null pattern are functions of the number of radiating elements, amplitude taper, lattice, and progressive phase shift [76]. Beamforming directs the transmitting antenna energy in a particular direction. Considering a fixed-size array employed for a given service in a certain region on the Earth, the beamforming characteristics control of the array are mainly a function of the complex-valued weight matrix, whose entries' magnitudes control the beamwidth in both planes and the SLL; on the other hand, the entries' phases of the matrix control the antenna beam scanning, and nulls [77]. Combining all the previously analyzed constraints to synthesize the beams in a multi-beam scenario will require proper optimization tool, computational time, computational resources, and power consumption, being limited in an in-orbit satellite. AI represents a promising solution to overcome these issues in realistic beamforming problems in SATCOM. First, implementing AI algorithms to beamforming allows recognizing underlying patterns, which would be inefficient to identify manually. This "black-box" characteristic of AI methods, especially NN, is an advantage since the performance of the deployed model does not depend on the antenna characteristics. Second, after training, NN can perform cumbersome operations in real-time, representing a promising solution for adaptive beamforming, where weights must be repeatedly calculated and conventional solutions are lengthy.

b) Conventional Solutions and Issues: The conventional solution applied to beamforming for satellite multi-beam application is an optimization problem, which consists of calculating the beamforming weights accurately to match the desired beam pattern [78], focusing the available transmit power on locations of interest while placing nulls at other directions, achieving a predetermined 3-dB main-beam width, and minimizing the SLL. In the literature, there are multiple solutions to beam synthesize [79]–[84]. Usually, a simple beamforming scenario, which is controlling the gain, can be easily simplified to a sum of the contributions of each antenna element with the required weight matrix as indicated by the array factor (AF) defined as 1

$$\mathrm{AF} = \sum_{m=1}^{M_x}\sum_{n=1}^{N_y} W_{mn}\mathrm{e}^{\mathrm{j}(m-1)(\kappa d_x \sin(\theta)\cos(\phi))}\times \\ \times\, \mathrm{e}^{\mathrm{j}(n-1)(\kappa d_y \sin(\theta)\sin(\phi))}\,, \tag{1}$$

where M_x is the number of elements in the x-direction, N_y is the number of elements in the y-direction, κ is the wave number, d_x is the period in the x-direction, d_y is the period in the y-direction, θ and ϕ are the evaluating angles, W_{mn} is the weight matrix entry of index (m, n), and j denotes the imaginary component. Now, if we consider a beam scanning angle (θ_0, ϕ_0) scenario, then the computation of the weight matrix can be done via

$$W_{mn} = \mathrm{e}^{-\mathrm{j}\kappa(md_x \sin\theta_0 \cos\phi_0 + nd_y sin\theta_0 \sin\phi_0)}\,. \tag{2}$$

Moreover, the previous weight matrix can be modified by applying an amplitude tapper like Hamming [85], Taylor [86], Hann [87], Chebyshev [88], or others to reduce the SLL and adjust the beamwidth. Complementarily, to avoid interference from another adjacent beam, it is convenient to add a nulling in a certain direction using, for example, [77]. A diagram example covering all the beamforming inputs and outputs is presented in Figure 5.

c) ML Solutions: Literature offers several contributions to the implementation of AI techniques and especially DL. Due to their fast response, rapid convergence rates, successful failure detection, and proactive decision capability, most adaptive beamforming adaptive beamforming (ABF)) techniques are now based on DL realizations. In [89], the neural beamformer utilizes RNN to search the optimal between three digital beamforming strategies. The work in [35], even if not explicitly targeting a SATCOM scenario, proposes a feedforward NN and RNN to compute the complex feeding weights for a linear microstrip antenna array. The work [90] exploits CNNs with offline training to match a specific radiation pattern and computes the array antenna excitations. CNN represents a faster alternative to conventional array synthesis techniques. [91] utilize a linear regression model to steer to predict the directions of arrival of the incoming signal to steer the array beam on the ground in the satellite direction. [92] implement a DNN to perform beamforming in a LEO system at sub-THz, where the atmospheric absorption is compensated by very large antenna arrays, that need to achieve very high gain in the desired direction via very narrow beamforming. The DNN beamformer is trained to mimic the actual output voltage generated by a TTD beamformer as the angle of arrival (AoA) changes at the receiver due to the rapid movement of the LEO satellite. In Fig. 6, we present two novel approaches to adaptive beamforming in SATCOM systems, Multi-Label Classification Neural Network (MLCNN), and Clustering and Classification Neural Network (CCNN), and compare them with a traditional Genetic Algorithms (GA) [93]. Our objective was to explore more efficient and real-time alternatives to GA, which, despite being effective, can be computationally expensive and time-consuming, making it unsuitable for real-time adaptation. Both approaches offer viable alternatives to GA for adaptive beamforming in SATCOM systems, significantly reducing execution times while maintaining high system performance [94]. The observed trends hold whether the data are normalized or not. All three algorithms exceeded the performance thresholds required to maintain high QoS, demonstrating only minor variations in efficiency among them. However, this is not the case when we talk about the response speed of the algorithm, which does make a big difference between algorithms suitable for real-time processing. Importantly, the operational implications of these algorithms, particularly in terms of real-time throughput, are significantly influenced by their computational efficiency. Our results indicate that the ML-based algorithms, MLCNN and CCNN, are substantially faster - over 95% - than GA when processing times are taken into account. This substantial speed advantage underscores the suitability of MLCNN and CCNN for real-time processing applications, especially in on-board satellite systems, where fast response times are

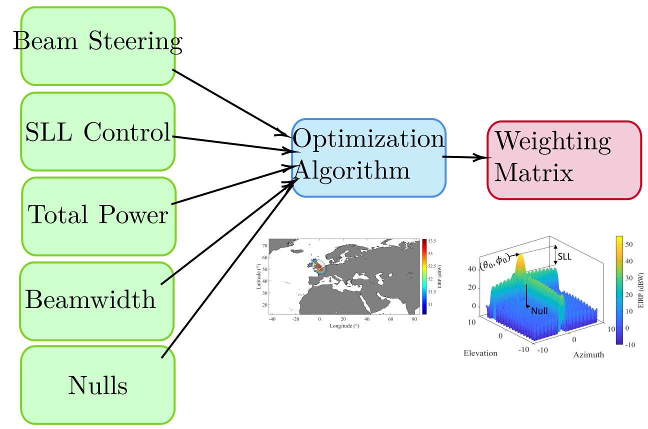


Fig. 5: Diagram with the inputs and outputs of a beamforming optimization.

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

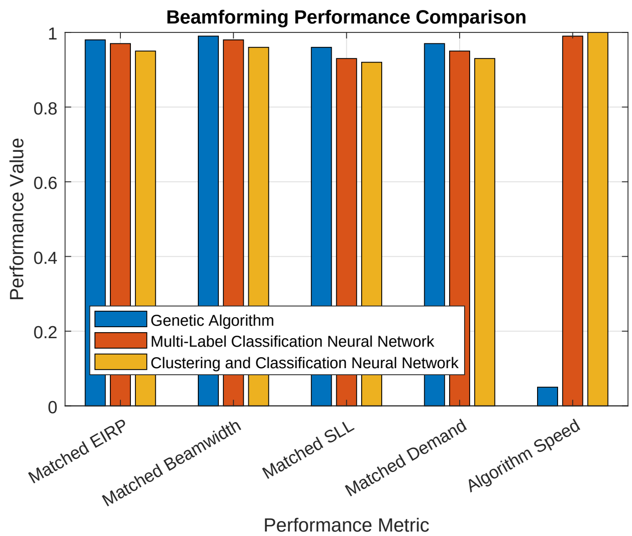


Fig. 6: Comparative analysis of traditional and ML-based methodologies for SATCOM Beamforming. The figure illustrates a comparison of beamforming performance across various metrics for three different algorithms: GA, MLCNN, and CCNN. The metrics evaluated include Matched Effective Isotropic Radiated Power (EIRP), Matched Beamwidth, Matched SLL, Matched Demand, and Algorithm Speed. Performance values are normalized and presented on a scale from 0 to 1. The GA, while generally showing superior performance in matched EIRP, beamwidth, SLL, and demand, is significantly outperformed in terms of algorithm speed by both NN approaches. This highlights the trade-off between execution time and overall performance, emphasizing the efficiency of NN-based methods for real-time adaptive beamforming.

Fig. 7: Beam activation scenarios. Antenna unconstrained activations (Left Figure), and Antenna constrained activation to a maximum of 6 times per antenna (Right Figure).

TABLE VI: Comparison between NN models and LSM

Metric	NN Model	LSM
Training Time	10 minutes	10 hour
Mean Response Time	10 ms	50 sec
Mean Divergence Main Lobe	0.4 degree	0.2 degree

critical. Data generated can improve efficiency in Direct Radiating Arrays (DRAs). Consider, for example, the necessity of establishing a multibeam configuration that allocates the requisite power across all antenna elements [93]. Referencing Fig. 7, we observe a scenario where seven beams are generated without imposing power constraints on each antenna element, alongside a scenario enforcing a power limitation. Specifically, this constraint stipulates that each antenna element may only be activated up to six times across the seven beams. The findings in [93] demonstrate that equitable power distribution among antenna elements is achievable, alongside the generation of ample training data conducive to ML application. This evidence strongly supports the integration of ML strategies in optimizing beamforming processes. The results of the radiation pattern generated for the beam activation scenarios in Fig. 7 are reported in Fig. 8.

Key Takeaway 1: Antenna Beamforming
Beside generating beamforming weights using a GA, we have implemented a Least Mean Squares (LMS) that computes the antenna elements weights while respecting the prescribed nulling and steering lobe (Fig. 9). The LMS algorithm has been interatively run to generate 5000 different pointing angles in radians between 45 deg and 75 deg, each representing different antenna element configurations that meet the defined constraints. The resulting weights serve as a reference for evaluating antenna performance and training ML model DNN. The labels are the weights and the inputs the pointing angles and the null directions.

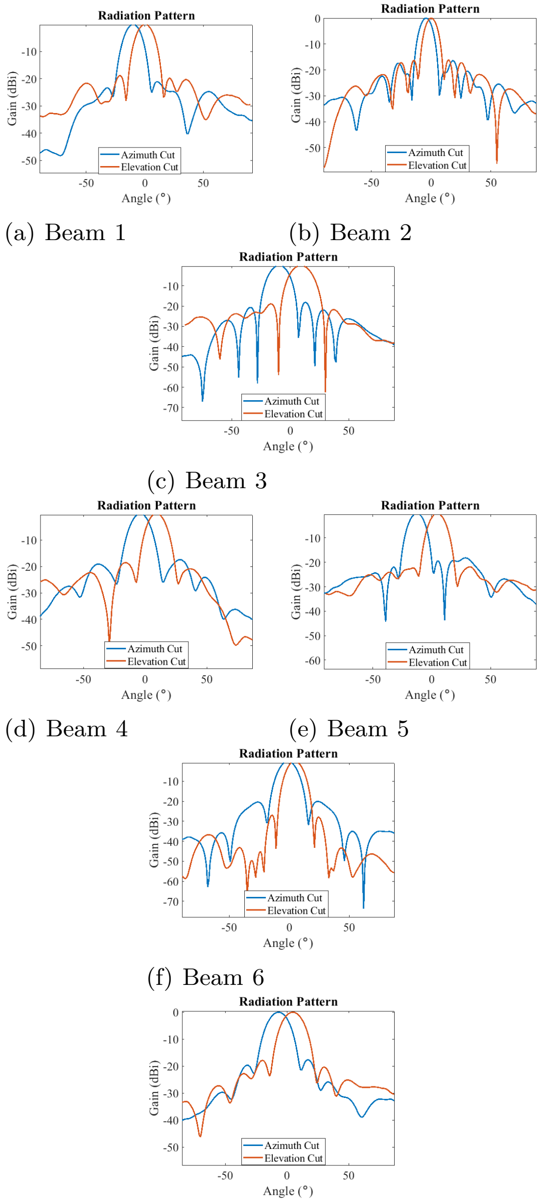
As beamformer, the DNN model performs with very high accuracy and much lower response time than that of the LMS algorithm. The time required to execute and obtain the beamforming matrix makes the LMS algorithm unsuitable for real-time applications. The supervised learning based approach significantly reduces the execution time (Table VI). This is because once the ML models have been trained, they can be used for inference with almost instantaneous response times, making them suitable for real-time adaptation. Another comparison between a DNN and traditional conventional algorithms can be found in [35].

The presented ML approaches go in the direction of taking advantage of ML techniques to have a sub-optimal tool for antenna beamforming able to ensure a fast response. Most of the ML models surveyed are offline NN/DNN approaches, since the main disadvantage of using NN/DNN approaches in SATCOM is the lengthy training process, to be conducted onboard or on-ground. However, despite the significant time required for training an NN in a multi-beam satellite scenario, the fast temporal response of NNs/DNN during inference is exploited for adaptive beamforming response.

2) Flexible Payload-Beam Hopping:

a) Motivation and Description: Beam Hopping (BH) helps SATCOM adapting to the time-varying communication demands which dynamically change due the time, mobility, and weather condition. Different from the quasi-static lighting in traditional multi-beam satellite systems, the satellite circularly illuminates a set of specific beams according to the generated schedule. The BH technology refers to the use of less numerous active beams in accordance with the design of the BH pattern to serve

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617



(a) Beam 1 (b) Beam 2

(c) Beam 3

(d) Beam 4 (e) Beam 5

(f) Beam 6

(g) Beam 7

Fig. 8: Azimuth and Elevation cuts of the resulting beams having an activation scheme.

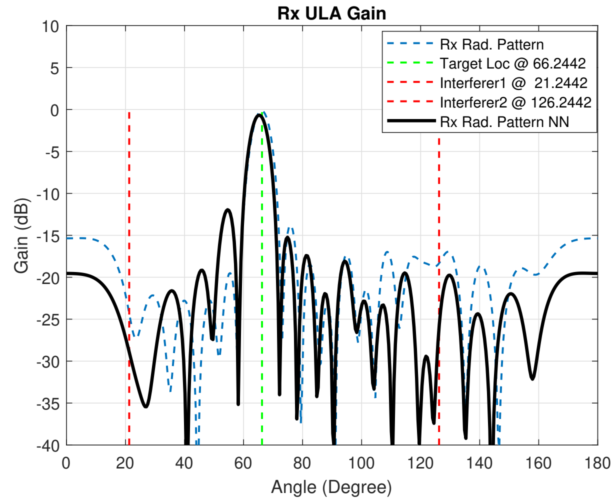


Fig. 9: Radiation patterns produced by a DNN with destination angle of 66°and SoAs received at respective AoAs equal to 21°and 126°.

the ground terminals within the satellite coverage area, herein, the available satellite resources can be further optimally used to provide services with the heterogeneous demands [95], [96]. The main difficulty in BH pattern design is the large search space for identifying the optimal patterns. That is, in order to find the optimal solution, the number of possible BH patterns to be searched increases exponentially with the number of beams [97]. In this context, ML appears as a promising technique that offers an alternative to design optimization algorithms for complex resource management in wireless networks.

b) Conventional Solutions and Issues: The SATCOM systems realize the BH technology the flexible payload where the design parameters can flexible configured [98]. The existing BH-related works aim to compose the beam switching and jointly optimizing beam pattern illumination mechanism with power/spectrum allocation and precoding/beamforming design. The work in [99] propose an iterative algorithm for BH illumination design while BH can also be optimized to minimize the transmitting power, as shown in [100]. Lin Chen et. al. in [101] have addressed a dynamic precoding-regarded beam-hopping design to minimize the cross interference and also avoid precoding whenever possible while it can satisfy all beam demands. The numerical simulations have illustrated the superior of the dynamic BH strategy to the traditional cluster-based BH mechanisms. [102] aims to jointly determine Linear Precoding (LP) vectors, BH, and discrete DVB-S2X transmission rates for the GEO SATCOM systems to minimize the payload power consumption and satisfy ground users' demands within a time window. Regarding the constraint on the maximum number of illuminated beams per time slot, the technical requirement is formulated as a sparse optimization problem in which the hardware-related beam illumination energy is modeled in a sparsity form of the LP vectors. To cope with this problem, an iterative compress-sensing-based algorithm is employed to transform the sparsity parts into the quadratic form of precoders. Authors in [103] design a dynamic baem hopping and beam position division for LEO SATCOM systems to shorten the packet queueing delay. In particular, this work aims to develop a novel mechanism to cover all users with the least number of beam positions in a set of beams which can be illuminated. The problem is first transferred into a p-center one, then the beam positions among the footprint of LEO satellites are determined dynamically by the user distribution and the traffic distribution. The work in [104] focuses on developing a novel cooperative beam-hopping mechanism for Non Geo-Stationary (NGSO) constellation consisting of multiple satellites. Regarding the load-balancing issue, the proposed algorithm in this work is designed to manage both intra-satellite interference and inter-satellite interference by designing beam-hopping patterns with spatial isolation characteristics.

c) Recent ML-based BH solutions and Future Directions: A number of recent works have also regarded employing the ML tools to several BH-enabled SATCOM schemes. Lei Lei et. al. investigates in [105] a DL method for BH optimization and to predict the number of elements in the beam pattern for BH and speed up the process of BH pattern selection and allocation. The same authors in [97] have explored a combined learning-and-optimization approach to provide an efficient, feasible, and near-optimal solution. The investigations are from the following aspects: 1) Integration of BH optimization and learning techniques; 2) Features to be learned in BH design; 3) How to address the feasibility issue incurred by ML. The numerical results have illustrated that the learning feature can enable a very high accuracy in predictions for the size of beam clusters that should be illuminated together to meet users' demands. In [106], the authors investigated the optimal fairness policy for beam hopping in DVB-S2X satellite regarding two main goals: minimizing the delay of real-time services transmission and maximizing the throughput of non-instant services transmission. To cope with the time-varying and unpredictable wireless channel issues, and differentiated service arrival rates in the multi-beam satellite environment, this work employed the model-free multi-objective DRL approach to learn and retrieve the optimal policy through interactions with the situation. To solve the problem with action dimensional disaster, a novel multi-action selection method based on Double-Loop Learning (DLL) is proposed. Moreover, the multi-dimensional state is reformulated and obtained by the DNN. Under realistic conditions achieving evaluation results demonstrate that the proposed method can pursue multiple objectives simultaneously, and it can also allocate resources intelligently adapting to the user requirements and channel conditions. The DRL-based approach is also exploited in [43] where a dynamic beam pattern and bandwidth allocation scheme based on DRL, which flexibly uses three degrees of freedom of time, space and frequency. Considering that the joint allocation of bandwidth and beam pattern will lead to an explosion of action space, a cooperative multi-agent deep reinforcement learning (MADRL) framework is presented in this paper, where each agent is only responsible for the illumination allocation or bandwidth allocation of one beam. The agents can learn to collaborate by sharing the same reward to achieve the common goal, which refers to maximize the throughput and minimize the delay fairness between cells.

3) Flexible Payload-Power Allocation:

a) Motivation and Description: In satellite systems, power consumption is a major limitation due to its significant impact on satellite mass and operation lifetime. Additionally, the upcoming on-board beamforming technology, which is highly power-hungry, presents a major challenge for on-board power optimization. In order to reduce power consumption, it is necessary to implement innovative techniques, and one feasible approach is to employ advanced power optimization techniques to reduce radiated power. In addition, conventional satellites provide connectivity for users through a multibeam footprint with uniform power allocation per beam. Notably, the payloads of the system are equipped with multiport amplifiers so that the power of the system can be divided across multiple beams. Hence, it is possible to use the remaining power in beams with lower traffic loads to those with higher traffic loads [107]. However, these flexible payloads require advanced power allocation algorithms to optimize the total transmit power based on each beam's traffic load [108].

b) Conventional Solutions and Issues: Several studies have been conducted to develop power allocation algorithms using classical methods such as analytical optimization and heuristic/metaheuristic methods. With analytical optimization, the algorithm provides an optimal or nearly optimal solution. In this context, in [109], an energy-efficient power allocation scheme has been designed to maximize the average rate ratio over the total consumed power. In addition, energy-efficient power allocation over multibeam satellite downlinks with imperfect CSI has been proposed in [110]. Furthermore, an energy-aware power allocation algorithm has been developed to jointly minimize unmet system capacity (USC) and total radiated power in [111]. In [112], a power optimization approach based on demand and channel quality has been evaluated to minimize the difference between offered capacity and demand while maintaining reasonable fairness for all users.

A metaheuristic method may not guarantee optimality, but it is well-suited to nonlinear, multi-objective, and NP-hard problems. In this context, Particle Swarm Optimization (PSO) is used in [113] to solve the power allocation problem in the multibeam satellite system, providing the minimum signal-to-noise plus interference ratio that the user terminal requires for reliable communication. Furthermore, a power allocation technique has been proposed in [114] to simultaneously minimize unmet capacity and power consumption in multibeam satellite systems. In [115], a game–based dynamic power allocation (AG-DPA) algorithm has been developed for multibeam satellite systems to match the offered capacity and per-beam demand.

The above-proposed method lacks flexibility in bandwidth allocation, limiting the ability to fully exploit flexible on-board payloads. This is addressed in [116]–[120] using analytical optimization and in [121], [122] using a metaheuristic technique to jointly optimize the power and bandwidth to match the capacity offered with the per-beam demand. Nevertheless, using analytical optimization and metaheuristic techniques for power allocation involves many optimization parameters, so these optimizations are very time-consuming. Furthermore, the algorithm needs to be performed frequently if there are slight changes in traffic requirements or channel conditions. Thus, the

TABLE VII: Summary of works on improving the performance of SATCOM medium layer use cases with ML. DLL is acronym for Double-Loop Learning

Low Layers				
Area	Ref	Application	ML approach	ML Improvement
Antenna Beamforming	[90] , [92]	array antenna current excitations	CNN , DNN	near real time antenna synthesis
	[35]	Beamforming weights microstrip antenna	DL, RNN	low complexity and temporal response
Beam Hopping	[105], [97]	BH enabled SATCOM	DL, Hybrid ML	BH optimization speed
	[106]	DVB-S2X satellite	DRL, DLL	higher throughput, lower delay
	[43]	BH enabled SATCOM	MADRL	higher throughput, lower delay

proposed power allocation algorithms may not be suitable for real-time applications. In this case, ML techniques can be vital to provide a low-complexity power allocation algorithm that adapts to the change of demand and/or channel conditions.

c) Proposed ML Solutions: Several researchers have proposed ML-based solutions to overcome the limitations of conventional power optimization techniques. Using a NN, [42], [123] proposes a classification algorithm that determines the power required for each beam to minimize the error between the offered capacity and the requested demand. Data is generated from a linear approximation function of spectral efficiency to train this NN. Since NN training is performed offline, the main advantage of this method is that it performs resource allocation at a low computational cost. However, the exponential relationship between the number of classes and the number of beams may increase the complexity of the computation and require further investigation. In [33], a CNN network is used to minimize the error difference between the offered capacity and the per-beam demand while saving unused satellite resources. For this, training data is generated from a realistic traffic model. The proposed algorithm in [33] shows better performance on the tradeoff of reducing capacity error and power consumption when compared with traditional resource allocation approaches. However, the algorithm depends on training data which is required to train the NN if there is a change in the traffic model.

A power allocation algorithm using DRL to maximize the system transmit data has been investigated in [124]. In this method, the satellite acts as an agent, while the traffic between beams acts as an environment. Additionally, the DRL state contains a combination of buffered data among beams, power allocations, and beam geographical distributions. Accordingly, the agent adjusts the power among the beams to maximize data transmission. The simulation results in [124] demonstrate that the proposed method outperforms heuristic power allocation methods in terms of the system's throughput. However, the power of each beam is adjusted to some discrete values, which may limit the system's performance.

In contrast, DRL for continuous power allocation in flexible high throughput satellites to minimize the overall unmet system demand and power consumption has been proposed in [125]. In this DRL-based power optimization method, the agent takes action (power allocation) given the state of the environment, which contains both the satellite model and demand per beam. For each action, a reward is assigned, modeled as a function of the difference between unmet system demand and power consumption. The proposed method is evaluated using time-series demand data provided by SES, and the authors demonstrate that the algorithm can match beam demand. Furthermore, the same DRL model as [125] has been used in [126] to compare with metaheuristic techniques. Conservative reward design, considering the implementation of safe exploration techniques [127] or implementing algorithms as constrained RL and constrained policy optimization could help the model guarantee the power limits.

4) Flexible Payload-Bandwidth Allocation:

a) Motivation and Description: A satellite with multi-beam technology generates narrow beams, each covering a specific geographical area. As the beams represent a specific area, the same frequency can be reused on non-adjacent beams. In traditional satellite systems, bandwidth is divided uniformly among the beams, with each beam sharing the total bandwidth equally. While some beams may have different demands, uniform bandwidth allocation may not be efficient in this case. Thanks to the emerging on-board digital payloads, satellite systems not only offer flexibility in power optimization but also allows flexibility in bandwidth utilization. Typically, a flexible payload consists of a channelizer, which digitally routes channels within beams by digitizing the signal. It has a variable number of ports, each capable of processing a specific amount of bandwidth (channel bandwidth) while providing switching capability at the subchannel level [107].

b) Conventional Solutions and Issues: Based on the characteristics of the beam demand, bandwidth allocation techniques can be categorized into three types:

1) Orthogonal frequency band assignment across adjacent beams: One example is a four-color scheme in which the total bandwidth is divided into four frequency bands (subchannels) [114], [128], [129]. However, this method is inefficient for heterogeneous demand, where some high-demand beams require more bandwidth while others need less. Furthermore, assigning orthogonal frequencies to some adjacent beams may not be necessary if their respective terminals are located near the center of the beams and their demands are low.
2) Semi-orthogonal frequency band assignment across adjacent beams: In this case, adjacent beams may

reuse the same frequency band. In [99], [116], subchannels (frequency bands) are iteratively assigned to each beam according to the traffic request while minimizing co-channel interference. Similarly, in [130], subchannels are allocated to each beam to maximize system throughput. This method uses the same subchannels between adjacent beams within a range where inter-beam interference is minimal, while other ranges use different subchannels. Alternatively, analytical optimization in [119], [120], [131], [132] and metaheuristics in [121], [122], [133] have been considered for bandwidth allocation based on the per-beam demand. However, it may be challenging to meet all beams that have a high demand using the techniques mentioned above.

3) Full frequency reuse can be applied to satisfy high beam demand while managing interference among the beams using precoding techniques [134], [135].

c) Proposed ML Solutions: Several researchers have proposed ML-based bandwidth allocation techniques. In [136], a dynamic channel allocation algorithm for multi-beam satellite systems is presented based on DRL, where the total bandwidth is divided into subchannels and assigned to each beam in order to reduce the blocking probability of the system. A discrete-time event system based on service arrival events is assumed and the satellite checks which channel to assign to the new arrival user terminal. In this case, the satellite serves as the agent, the action determines which channels to allocate, and a positive reward is provided when the new service is satisfied. On the other hand, a DRL-based approach for energy-efficient channel allocation in the satellite internet of things has been studied in [137]. This method involves finding an optimal channel allocation strategy that allocates the limited channels to users on the ground while saving transmitting power in the long term. In [137], the satellite is viewed as an agent, and the user requirement and location represent the environment's state. Based on the environment's state, the agent allocates channels. In this method, the reward is considered the sum of the system's power consumption and service-blocking rate. Based on the numerical results in [137], the proposed method has better energy efficiency than traditional algorithms.

In [138], an algorithm for time-frequency resource allocation with DRL has been investigated to maximize the number of users and system throughput. In [138], the ground gateway is considered as an agent, as well as the number of time-frequency resource blocks and the user requirements as the environment. Consequently, the agent allocates the resource block while examining the state of the environment. Based on the simulation results presented in [138], the proposed DRL method gives better resource utilization with low computational complexity compared to the GA and Ant Colony Optimization (ACO). Similarly, cooperative MADRL to allocate bandwidth with flexibility in time, space, and frequency has been investigated in [43].

Generally, several studies have investigated the use of ML applications to maximize system quality of service [139], spectral efficiency [140], transmission efficiency [141], and resource utilization [142], [143]. While [144] applies multi-objective RL to manage multiple systems' performance attributes such as throughput, bandwidth, spectral efficiency, bit error rate, power efficiency, and power consumption. On the other hand, in [145], a demand-aware bandwidth and power allocation algorithm have been proposed based on analytical optimization and DL. Thus, analytical optimization enables bandwidth and power allocation, while DL can speed up computation.

Fig. 10 delves into radio resource management, contrasting traditional algorithms based on proportional power allocation (PPA) and assignment game-based dynamic power allocation (AG-DPA) with ML approaches, specifically NN classification and CNNs. The PPA algorithm is critiqued for its inadequacy due to a proportional power management system that neglects inter-beam interference. As traffic demand scenarios become more complex, the effectiveness of classification via NN diminishes. The CNN emerges as the superior algorithm, offering the best compromise between minimizing capacity error and maximizing energy savings, whereas the AG-DPA algorithm, while maximizing energy savings, compromises on capacity error normalization.

5) Flexible Payload-Beamwidth Allocation:

a) Description and Motivation: The allocation of beamwidth in SATCOM systems plays a crucial role in meeting user demand requirements, particularly in scenarios where users are located in remote geographic areas such as airplanes and ships. These mobile broadband users have dynamic traffic demands that cannot be efficiently supported by the conventional fixed beam pattern and footprint planning of high-throughput satellites [146]. Additionally, with the non-uniform distribution of user terminals and varying traffic demands expected in the next generation of SATCOM systems, there is a need for adaptive beamforming capabilities and beam pattern planning [147], [148].

The objective of beamwidth allocation is to minimize KPIs such as the gap between offered and required capacity or the Coverage Error. By defining system characteristics like service area, satellite orbital position, bandwidth, and power per beam, along with technical constraints, design parameters can be determined. These parameters include possible beamwidth values and antenna orientations [147].

To effectively allocate beamwidth, the average traffic demand in the service area is studied and divided into regions. Each region is assigned a specific beamwidth to accommodate the predicted traffic demand distribution. Narrower beams are assigned to regions with higher traffic demand, while larger beams are used for lower traffic demand areas.

The coverage is designed based on different beam orientations, taking into account technological constraints. Evaluating the SATCOM link conditions, such as the number of beams, capacity offered per beam, overall satellite

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

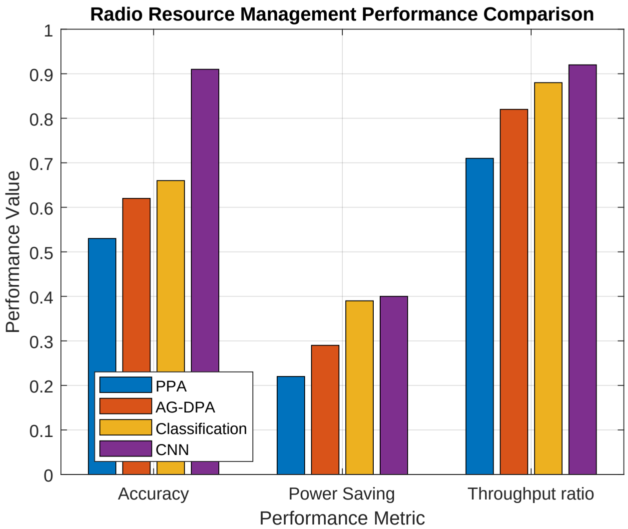


Fig. 10: Comparative analysis of Radio Resource Management (RRM) performance across several metrics for four different algorithms: Proportional Power Allocation (PPA), Assignment Game-Based Dynamic Power Allocation (AG-DPA), Classification, and CNNs. The performance metrics evaluated include Accuracy, Power Saving, and Throughput Ratio, with performance values normalized on a scale from 0 to 1. The PPA algorithm shows lower performance in all metrics, reflecting its inadequacy due to neglecting inter-beam interference. As traffic demand scenarios become more complex, the effectiveness of the Classification algorithm decreases. The CNN stands out as the superior algorithm, offering the best balance between minimizing capacity error and maximizing energy savings. In contrast, the AG-DPA algorithm, while achieving high energy savings, compromises on capacity error normalization. This comparison underscores the advantages of CNNs in handling complex RRM scenarios effectively.

capacity, and relevant KPIs, allows for the calculation of the cost function at each time instant t.

b) Conventional Solutions and Issues: Traditional approaches to beam pattern planning in SATCOM systems have focused on ensuring global coverage by using fixed beam footprints. Some studies have examined the feasibility of beam arrangements and antenna requirements, but they do not adequately address the challenges posed by non-uniformly distributed user terminals and varying traffic demands [76], [149]–[152].

Recent research has explored adaptive schemes to accommodate fluctuations in traffic demand. Topics include global resource management for dynamic beam steering based on QoS requirements and user channel conditions [153], optimization of beam directivity and transmit power to enhance system performance [154], adjustment of satellite transmit antenna aiming point to optimize signal-to-noise power ratio and minimize interference [155], and joint optimization of beams, beamwidth, power, and bandwidth allocation to match data rate with traffic demand [156]. However, these studies do not consider adaptivity in terms of flexible beam size and position during beam pattern and footprint planning, nor do they fully address the mobility aspects of non-uniformly distributed users.

Additionally, advanced fixed multibeam patterns and footprint plans have been studied to highlight their limitations in supporting non-uniformly distributed user terminals and varying traffic demands [148]. These studies propose adaptive multibeam patterns with flexible beam sizes and positions based on spatial clustering of users, aiming to increase the flexibility of high-throughput satellite systems.

c) Proposed ML Solutions: In recent years, ML techniques have been proposed as a means to enhance beamwidth allocation in SATCOM systems. For example, a CNN was employed to solve the resource management problem, including beamwidth management, by minimizing the error between offered and required capacity while optimizing resource utilization [33]. However, this approach relies on the traffic model used during training and may require retraining when traffic behavior deviates from the model.

RL algorithms, such as Q-Learning, Deep Q-Learning, and Double Deep Q-Learning, have also been investigated for managing available resources, including beamwidth, in flexible payload architectures [157]. These algorithms were compared based on their performance, complexity, and added latency. Furthermore, the use of decentralized cooperative multi-agent (CMA) distribution was shown to outperform single-agent approaches in multibeam scenarios.

Key Takeaway 2: Flexible payload
It is worth noting that while ML has shown promise in optimizing beamwidth management, there is still room for further exploration, particularly regarding ML's potential in enhancing geographical positioning as an additional resource. ML approaches can improve the cost function, reduce time and complexity by leveraging the vast search space, and overcome the limitations of conventional optimization techniques.

Most methods mentioned for bandwidth allocation use combinatorial optimization, resulting in longer computation times as the number of beams or subchannels increases. Furthermore, re-executing the algorithm may be required if traffic requirements or channel conditions change slightly. In this situation, developing an algorithm based on ML that can adapt to changing traffic and/or channel conditions could be useful. DRL is the most used method in bandwidth and power allocation, where the agent is placed at the gateway or not specified. This comparison shows that DRL is the most appropriate option when time is critical, and a solution is needed in seconds. For online learning, as in RL techniques, it is of critical importance in the future to evaluate the impact of the training on the satcom system, as for the energy consumption and the environmental impact.

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

Implementing ML for flexible beamwidth to enhance flexibility in geographical positioning has yet to be explored as another possible resource in addition to bandwidth. In that sense, it is expected that ML can enhance the gain in the cost function, a reduction in the time and complexity required because the search space is huge for conventional optimization techniques.

Lessons learned in the area of the Flexible Payload include:

- Ensuring Limited Transmit Power Constraint in ML Algorithms: maintaining the constraint of limited transmit power is critical to power allocation in SATCOM systems. ML algorithms, particularly those involving optimization techniques, can be designed to include this constraint as a fundamental part of their objective function. For example, the training data can be curated in supervised learning models to reflect scenarios adhering to power constraints, ensuring the model learns to operate within these limits. In DRL approaches, the reward mechanism can be structured to penalize actions leading to power constraint violations, thereby guiding the model to make decisions that respect the transmit power limits. While exploration plays an important role in the success of RL, agents operating in real world environments must account for safety constraints and be able to assess risks. In addition to reward shaping in RL, as a first practical method to guarantee transmit power limits some studies propose adding a scalable safety layer on top of the policy to correct unsafe actions [158]. In [125], the action computes the minimum satellite power to be allocated to each beam to satisfy the traffic demand of the beam. If the demand cannot be met, this optimal power equals the maximum allowed power P_B^{max}. The action of the proposed DRL framework (value of transmission power) taken by the DRL agent is cut between zero and P_B^{max} to ensure the transmission power limits are met.
  Another method is proposed in [159], where an exploration NN is added in the proposed RL algorithm to prevent the system from spending time exploring radio parameter combinations that will result in low performance or constraint violations. The exploitation NN learns actions best suited for the dynamically changing channel conditions. In this way, the training is performed safely until convergence is reached and the exploitation phase can start. Finally, we mention the work in [160], where the energy constraint is not considered in the reward of the proposed DDPG RL algorithm, but in the state space, as the current energy available on the satellite, and in the action space, where the proportion of allocated power is considered together with the reserved power.
  When considering power constraints handling with DRL, normalization can generally improve the generalization capabilities of the DRL model bringing the various power-related inputs into a common, normalized range. In addition, normalization can help balance the exploration-exploitation trade-off by ensuring that the agent's actions are appropriately scaled, potentially leading to more efficient exploration within the allowed power limits [125]. The work in [125] focuses on optimizing the power allocation that satisfies the system demand while respecting the maximum power constraint for each satellite beam. The reward function of the DRL algorithm consists of a first element that tries to satisfy the demand, while the second responds to the need to reduce the power without underserving that demand. Both reward elements are normalized by the overall demand and the total optimal power. In this way, these normalized values make it easier to compare and interpret the relative importance of different factors in the agent's decision-making process.

6) Link Adaptation:

a) Motivation and Description: Adaptive Coding and Modulation (ACM) techniques are among the most successful fade mitigation techniques for wireless links. The channel conditions in SATCOM links, such as rain, scintillation and delay, make it difficult for the estimation signal for feedback to choose the most suitable Modulation and Coding scheme at all times. ACM is easy for a single link without interference, where a pilot signal can measure the channel and report back to the receiver [161]. However, the innate delay of satellite links changes the problem, especially in multi-beam satellites with many channels to estimate. There is an evident "dead time" between the fade event and its corresponding ACM reaction. This dead time may last between 600 and 800 ms and is caused by the two hops over the satellite and additional averaging delays. Frame errors might appear during this period if the SNR decreases. In addition, emerging SATCOM scenarios with NGSO and GEO increase the interference between systems, whereas ACM can improve communication performance by avoiding interference as far as possible. ACM employment includes as benefits greater distances without errors, the use of smaller antennas that save on mast space, and higher availability to provide better link reliability. The usage of ACM techniques aims to improve SATCOM links' operational efficiency by increasing network capacity over the existing infrastructure while reducing sensitivity to environmental interferences.

b) Conventional Solutions and Issues: Link adaptation becomes more challenging when an interference channel is considered, or multiple channels are present, including multiple-input multiple-output (MIMO) systems. The authors in [162] and [163] have considered the power adaptation for interference channels when the complete CSI is unavailable at each transmitter. Remarkably, in [163], different levels of coordination between transmitters are evaluated. From the point of view of emerging scenarios, an ACM scheme suitable for integrating the satellite in 5G networks is proposed in [164] based on 21 MODCOD schemes and different thresholds for SNR grouping. ACM techniques for high-rate transmitters are developed on

FPGA in [165] and proposed for LEO satellites. This proposal reaches a spectral efficiency of 7.068 bps/Hz with a code rate of 0.8889 in the highest rate mode. For the optical feeder link, time-packing is used as ACM considering low-order M-ary Pulse Amplitude Modulation (M-PAM) as shown in [166] where time-packing enables a finer granularity on the LA capability of the optical link, enabling adjust its SE according to the moderate attenuation that thin cloud layers introduce. [167] uses precoding at the gateway side and SINR estimation at the terminal to address the issue of LA or ACM in a multi-user and multibeam satellite. This strategy includes a scheduler among different SNIR values and with imperfect CSI to maximize the similarity of two channels in the same frame. The literature shows two main problems to be solved in LA with the new SATCOM paradigm. On the one hand, the wide margin that the Q/V and W frequency bands require for new mega-constellations and, on the other, the amount of information that must be estimated in multibeam satellites. We would like to clarify that the blind-identification does not typically occur in SATCOMs, because the modulation and coding scheme used by the TX is coded in the Physical Layer (PL) framing. In particular, the PL header contains information on the PLFRAME duration and structure, the modulation and coding scheme, and the presence or absence of pilot symbols. The receiver can always decode the header because it is always modulated into a $\pi/2$BPSK symbols (lowest modcod).

c) Proposed ML Solutions: The application of ML for LA has been considered in [168] and [169] using Bayesian methods focused on NN, which shows performance gains over the commonly used ACM selection based on effective SINR. The work presented in [170] focuses on applying ML to CSI prediction in SATCOM and using the improved prediction results to optimize system capacity. The different tested ML techniques demonstrate the improvement in system performance and the feasibility of deploying an ML-based prediction framework. The ML-based CSI prediction model provides an average capacity increase of up to 10.9% with acceptable overhead. The authors in [171] propose a neural episodic control (NEC) algorithm from the DRL group as an ACM scheme for Inter-Satellite Communication Link. The proposed scheme adjusts the modulation and coding scheme region boundaries with a differentiable neural dictionary of the NEC agent, which enables the effective integration of the previous experience. The ACM proposed in [172] utilizes an online random regression forest (ORRF) to predict time series of SNR values aiding the ACM switching decisions, introducing adaptive techniques for satellite links on Q/V-Band. The ORRF-based approach could outperform the classical approaches in terms of SE, and the parameterization of the ORRF is simpler and needs less knowledge of the channel properties than the discussed classical ACM approaches.

7) Spectrum Sensing, and Interference Detection and Classification:

a) Motivation and Description: The usage of spectrum in current day SATCOM follows a rigid and fixed spectrum allocation management paradigm. However, since the number of satellite and terrestrial services that require an ever-increasing bandwidth grows while the spectrum resource is fixed, the existing paradigm is inefficient. A direct implication is that the available spectrum has to be shared and reused among those services. Besides interference, which is due to sharing the spectrum, there are intentional jamming sources that try to disrupt the Quality of Service (QoS) of SATCOMs systems. Both types of interference require detecting and classifying interference signals to take the appropriate measures. This will require a two-step process: 1) observing/collecting data, and 2) processing these data to decide on the current status of the spectrum.

b) Conventional Solutions and Issues: To address the issue of spectrum sharing and the entailed interference management issue, many works in the literature focus on CR SATCOM, where the coexisting systems are divided into primary and secondary, and the secondary system has to operate within limits specified by the QoS of the primary system. CR is divided into overlay CR and underlay CR networks [173]. In the former, the secondary system relies on detecting and using white spaces of the spectrum (parts of the spectrum that are not currently being used by the primary system), whereas in the latter, the secondary system relies on adapting the transmission parameters based on the maximum interference the primary system allows at its receivers to maintain the required QoS [174]. These systems, however, require collaboration and sharing of information between the primary and secondary systems, which is usually done via a third-party (centralized) manager, which adds complexity, overhead, and cost. Another approach to manage interference while sharing the spectrum is interference detection and mitigation, where conventionally, a receiver analyzes the received signal based on some a priori statistical knowledge of the desired and interference signals as well as the channels [175], and takes actions whenever interference is detected, like changing the transmission carrier frequency and sub-band. In [176], the authors studied distributed Dynamic Spectrum Sharing (DSS) for a system where Geosynchronous Orbit (GSO), NGSO, and terrestrial networks share the same spectrum in both downlink Ka-band (17.7-19.7) GHz, and uplink Ka-band (27.5-29.5) GHz, where terrestrial networks are the incumbent (primary) users that consist of 5G fixed wireless access and microwave links. The multiple access technique assumed for satellite-related links is Multi Frequency-Time Division Multiple Access (MF-TDMA), whereas for terrestrial networks, it is Frequency Division Multiple Access (FDMA). Two techniques were proposed: collaboration protocol, where nodes from different systems share information they capture from other nodes participating in the collaboration, and spectrum sensing, where each receiver makes decisions on spectrum allocation based on locally acquired energy maps of the spectrum by processing the raw I/Q received

TABLE VIII: Summary of works on improving the performance of SATCOM low layer use cases with ML. ORRF means online random regression forest

Low Layers				
Area	Ref	Application	ML approach	ML Improvement
Bandwidth Allocation	[136]	multi-beam SATCOM	DRL	blocking probability, spectral efficiency
	[137]	Satellite Internet of Things	DRL	energy efficiency
	[138]	multi-beam SATCOM	DRL	resource utilization, complexity
	[145]	traffic congestion in SATCOM	DL	computation time
	[43]	Beam Hopping Satellite Systems	multi agent DRL	resource utilization
	[139]	LEO SATCOM	DQN	QoS
	[140]	multibeam GEO	DRL	Spectral Efficiency
	[141]	limited satellite-based radio resources scheduling	cooperative multi agent DRL	Transmission Efficiency
	[142], [143]	LEO network	LSTM, CNN, DL	resource utilization
Beamwidth Allocation	[33]	resource management for flexible payload	CNN	cost optimization
	[157]	resource management for flexible payload	QL, DQL, DDQL	complexity, and added latency
Link Adaptation	[168], [169]	BCIM OFDM	NN	Improved SINR
	[170]	DVB-S2, DVB-RCS2 SATCOM links	MLP, random forest, Adaboost, kNN	capacity increase
	[172]	Q/V-Band Satellite Links	ORRF	spectral efficiency, lower complexity

data. An advantage of the latter is that the receiver can detect known and unknown interference, while only interference sources shared through CP are detected in the former technique. Another advantage of decentralized spectrum sensing is that information exchange happens only between communicating entities for resource reallocation or release, which reduces the overhead of sharing information. Although the spectrum sensing technique does not require exchanging information from entities of other systems, it requires changes in the radio modem to integrate spectrum sensing. Some satellite links, such as Global Navigation Satellite Services (GNSS) systems, require anti-jamming capabilities. Conventionally, GNSS uses postprocessing techniques that rely on the statistical characterization of the signals to activate interference mitigation procedures since different countermeasures are appropriate to different jamming signals [177]. These approaches can be effective when the jamming signals are known, and the number of jamming sources is limited. However, estimating the probability density functions for all hypotheses becomes more complex as the number of interference signal types increase.

c) Proposed ML Solutions: Data-driven approaches employing ML algorithms are considered an alternative way of detecting interference [178], where complexity is transferred offline in training the algorithm instead of the online complexity in processing the received signal in the conventional approaches. In [178], the authors considered a two-stage system based on the DL model, wherein in the first stage, an autocorrelator is used to detect the interference signal. In the second stage, DNN classifier is employed to classify the interference signal from three different well-known standards, namely: LTE, UMTS, and GSM, while the incumbent system is a DVB-S2 system. This means that one classifier can detect and classify the interference signals instead of different classifiers for different signals. Regarding Anti-Jamming capabilities, in [177], the authors studied k-nearest neighbor (KNN) ML algorithm in detecting and classifying chirp jamming signals to GNSS systems, which is a challenging task using traditional approaches due to their variety, that requires post-processing of the signals and human-driven analysis, thus limiting their timely awareness and response jamming attacks. On the other hand, ML-based approaches can detect and classify the jamming signals automatically, which makes them better candidates in scenarios where timely awareness and response are required.

Key Takeaway 3: Link Adaptation, Spectrum Sensing
An improvement of the CSI prediction in the satellite network is expected with the ML algorithms that will help realize ACM, predicting the most appropriate ACM to optimize system capacity for given channel conditions. This strategy will enable us to develop a more efficient ACM mechanism. In conventional approaches for spectrum sensing, the data-processing stage happens online and is designed by domain experts based on the specific knowledge of the signals' characteristics. On the other hand, in ML approaches, the algorithm learns the characteristics of the signals by training on a sample training data offline. Once the algorithm learns the characteristics well enough to differentiate between the different states of the spectrum, the resulting model is deployed online. However, real-time spectrum sensing decisions to increase the overall throughput would also be enabled by online methods, still not available in literatures. Moreover, spatial spectrum scenarios will have to be considered together in SAGIN architecture.

8) Intersatellite Synchronization:

a) Motivation and Description: Inter-satellite synchronization is a new open challenge triggered by the boom

TABLE IX: Summary of works on improving the performance of SATCOM low layer use cases with ML. FDML is first difference aware ML.

Low Layers				
Area	Ref	Application	ML approach	ML Improvement
Sensing	[179]	wireless signal identification	CNN	better accuracy
Interferemce	[178]	frequency domain interference detection	autoencoder, DNN	general applicability
	[177]	Anti-Jamming	KNN	lower time detection
	[180], [181]	frame synchronization	CNN, DNN	detection accuracy
Intersatellite	[182]	sampling frequency and time offset compensation	FDML	attack detection accuracy
Synchronization	[183]	carrier synchronization	LSTM	lower synchro time
	[184], [185]	characterization of phase noise	Bayesian filtering	overall performance
	[71]	GEO satellite precoding matrix calculation	autoencoders	gain in SINR
Precoding	[145]	traffic congestion in SATCOM	DL	computational time
	[186]	multi-beam GEO	Supervised Learning	higher UE rate
Link Quality	[187], [188]	Channel prediction	DL	Fast and low cost
Prediction	[189], [190]	with weather information	LSTM, DL	real-time fading estimations

of small satellites grouped in Distributed Satellite Systems. Currently, Distributed Satellite Systems are considered in multiple applications, from space communications to remote sensing. In the first case, the main advantages of distributed over monolithic SATCOM systems could be the increment of the system capacity and the reduction of the transmission power. Meanwhile, distributed Earth observation satellite missions can achieve higher spatial resolution requirements than single-platform architectures. However, the Distributed Satellite Systems should satisfy strict time and phase synchronization requirements to provide such performance enhancement.

b) Conventional Solutions and Issues: Conventional solutions for inter-satellite synchronization can be classified as Closed-loop or Open-loop methods based on the feedback from the receptor or target. The Closed-loop methods require a communication channel to transmit the feedback information between the external node and the Distributed Satellite System, which makes these methods more suitable for communication systems. Whereas in Open-loop, synchronization is achieved without the participation of any node other than the distributed satellites, as typical remote sensing applications require. In addition, we consider the communication between the elements of the Distributed Satellite Systems as an additional way of classification. It includes (I) synchronization algorithms based on the exchange of information among the distributed satellites, which can be done as a two-way message exchange or (II) as a broadcast, i.e., one-way communication. (III) Another option is to synchronize without any communication among the elements of the Distributed Satellite Systems by relying the control on a node out of the Distributed Satellite System. Both classifications can be superimposed or combined

c) Proposed ML Solutions: Works in carrier synchronization [183], and the characterization of phase noise [184], [185] have shown promising results to address problems related to synchronization in end-to-end-communication SATCOM systems using ML techniques.

ML techniques increase the accuracy of the amplitude and phase noise characterization of frequency references, which are essential elements for the synchronization of Distributed Satellite Systems. In this regard, a Bayesian filtering-based framework combined with expectation-maximization was used to characterize the noise of lasers in [184]. The carrier synchronization was experimentally demonstrated using the proposed framework in low Signal-to-Noise Ratio (SNR) scenarios.

In the context of integrated 5G and SATCOMs utilizing Orthogonal Frequency-division Multiplexing (OFDM), authors in [185] proposed a Cyclic-Prefix-based multi-symbol merging blind synchronization algorithm to enhance the timing accuracy. Besides, the authors proposed an improved synchronization method to correct time-frequency errors in 5G SATCOM integration scenarios accurately. Another example of ML used in frequency hopping-frequency division multiple access (FH-FDMA) SATCOMs is the challenging synchronization between Dehop-rehop Transponder (DRT) and ground equipment using different hopping sequences for the uplink and downlink. In this regard, authors in [183] proposed a novel ML-based method to synchronize the Frequency Hopping signal by utilizing serial search for coarse acquisition and LSTM network for fine acquisition. The main objective of the proposed method was to reduce the synchronization time.

9) Precoding:

a) Motivation and Description: Interference between adjacent beams strongly limits the overall system throughput. Consequently, it is of utmost importance to apply advanced interference mitigation techniques at the receiver, e.g., multiuser detection, or at the transmitter, i.e., precoding.

Due to the popularity of multiuser multiple-input multiple-output (MU-MIMO) techniques in terrestrial communications, together with the launch of the superframe structure in the DVB-S2X standard, the SATCOM community has started to evaluate and implement precoding techniques in multibeam SATCOM systems.

The most popular precoding design in SATCOMs is the low-complexity Regularized Zero Forcing (RZF) precoder, which is designed as follows:

$$\mathrm{W}_{\mathrm{ZF}} = \eta \cdot \tilde{\mathrm{H}}^{H} \left(\tilde{\mathrm{H}}\tilde{\mathrm{H}}^{H} + \alpha \mathrm{I} \right)^{-1}, \quad (3)$$

where η is a normalization factor ensuring that the output signal stays within the power limits. For a system-level power constraint, $\eta = \sqrt{P_{\mathrm{tot}}/\mathrm{Trace}\left\{\mathrm{W}_{ZF}\mathrm{W}_{ZF}^{H}\right\}}$ such that the sum of the norm of the precoder vectors inW_{ZF} is equal to P_{tot}, i.e. $\sum_{n=1}^{N} \|\mathrm{w}_n\|^2 = P_{\mathrm{tot}}$. The regularization factor α is an arbitrary number, which is usually considered equal for all users and proportional to the inverse of the expected signal-to-noise ratio [191].

In RZF, the precoding matrix is calculated once per frame period, and the computation of W_{ZF} is mainly driven by the matrix inversion process.

b) Conventional Solutions and Issues: The asymptotic complexity when assuming the Cholesky decomposition method is given by $\frac{1}{3}N^3$ flops [192], where N is the number of beams. Even if the number of beams is high, the standard is limited to 32 unique Walsh-Hadamard (WH) sequences. Therefore, the receiver can discriminate the signals coming from the 31 nearest interfering beams, and the complexity is upper-bounded by $\frac{1}{3}32^3$. It is to be noted that such inverse operation needs to be re-calculated as soon as the scheduled users change (i.e. when the channel matrix changes). All in all, such computation is considered computationally intensive for conventional systems. Different approaches have been investigated to mitigate this challenge, e.g. precoding matrix nullification, which consists of nulling-out irrelevant coefficients.

c) Proposed ML Solutions: In [71] the GEO satellite precoding matrix calculation was studied and evaluated using a two-step procedure involving autoencoders. The first step tries to learn the relationship between the real channel and the estimated channel matrix, i.e. understand the proper parametrizations to cover all the relevant information about the real channel matrix and the estimated channel matrix, respectively. The second step starts with the already inverted, estimated channel matrix from the simulation framework and predicts the alternative precoding matrix. Therefore, the second step does not need to learn the complex matrix inversion performed in the simulator framework but can focus on the remaining projection. Once the individual steps are solved, the combined approach estimates the ML-based precoding matrix directly from the estimated channel state matrix of the terminals. According to ESA MLSAT project reports, the proposed AI-based approach showed a 3dB gain in mean SINR.

Some works like [145], [186] have considered precoded GEO satellite systems and learning-based techniques but not directly to calculate the precoding matrix but to optimize the resource allocation assuming a fixed linear precoding matrix.

10) Link Quality Prediction:

a) Motivation and Description: Satellite services are being deployed in higher frequency bands to provide higher capacities. Ka and Q/V show substantial excess attenuation in atmospheric events, especially rain. As a result, techniques for mitigating satellite link unavailabilities, such as automatic power control, gateway switching and adaptive modulation and coding schemes, have been studied in recent years. As the implementation of the mentioned fade mitigation approaches requires a non-negligible delay, link quality prediction techniques become mandatory. Indeed, for the efficient deployment of pre-emptive fade mitigation techniques, satellite systems shall accurately track the link quality.

While the terminal segment predictions require a time window similar to the propagation delay, the ground segment usually needs longer time windows for performing mission-level operations such as gateway switching. Bearing this in mind, while the terminal channel predictions can rely on former and current channel values, addressing longer time windows usually require external information such as weather predictions. Channel samples become uncorrelated with time lags similar to a few seconds.

Mobile satellite services vendors have addressed the terminal channel variations for many years as it was the main shortcoming of terminal capacity. Those systems generally rely on margins so that modulation, coding scheme, and transmitted power are selected considering a potential decay of the channel magnitude. On the contrary, ground segment systems, whose cost severely relies on high power amplifier and antenna size, focus on switching mechanisms when their fade mitigation techniques do not circumvent the channel degradation.

b) Conventional Solutions and Issues: The propagation community in different papers carefully addressed the prediction of channel values [193]–[195]. Mathematical models behave well in short-term predictions and offer good results in temporal horizons below one minute. However, the operational gateway switch requires a few minutes, so channel predictions shall consider a longer prediction window than those in the mentioned mathematical models.

The first attempt to consider several minutes of gateway prediction can be found in [196]. This seminal paper utilizes a Bayesian approach to consider a priori forecast weather data to attempt to predict the channel values in several minutes time windows. Prediction accuracy is linked to weather forecast accuracy as rainfall rate is the determining feature of strong satellite link fading events.

c) Proposed ML Solutions: Due to the exponential interest in ML solutions, channel prediction and, in general, radio propagation modelling techniques have been revisited in [197]. The goal is to move from a model-based approach to a data-based approach which can eventually embrace high-complex scenarios while preserving a relatively low computational complexity.

This is the case of the recent works in [187]–[190]. The goal of these works is to rely on DL time series prediction known approaches and apply them to channel prediction. Generally, the model boils down to

$$g(\mathbf{h}, \mathbf{w}; \theta) = \hat{h}', \tag{4}$$

where $\hat{h}'$ is the predicted channel value, $\mathbf{h}$ is a vector containing the staked previous channel values, $\mathbf{w}$ is the external weather features, and θ is the deep neural parameters to be learnt in order to perform the prediction efficiently. Remarkably, the external weather information results to be a critical aspect in the works [187], [188], [190], which can be either a set of RADAR images or the current rainfall rate.

While (4) shows a good performance in below few minutes time horizon prediction, addressing longer time windows could eventually require weather predictions. This is reported in [198], where external rainfall prediction techniques are utilized as a priori information for performing the channel quality prediction in long-term periods.

11) Coding:

a) Motivation and Description: Coding schemes are a crucial element of modern digital communications systems. Convolutional Codes, Turbo codes, Low-Density Parity-Check (LDPC), Reed-Solomon or Polar codes are examples of Forward Error Correction (FEC) algorithms used in different communications standards such as DVB or 3rd Generation Partnership Project (3GPP) (Fourth Generation (4G), Fifth Generation (5G) and future 6G) for channel coding. From the point of view of SATCOM, reducing power consumption and processing time is vital due to its repercussion on the payload size and, consequently, on the cost. Also, satellites must reduce latency and delay to integrate with terrestrial networks. Reducing the processing time favours the previous reduction or compensates for the least latency and delay innate to SATCOM's nature. All these challenges are the objective for future regenerative payloads, reducing complexity in HTS and, on the other hand, reducing the sizes of the payloads and improving the NGSO small satellites.

b) Conventional Solutions and Issues: Typical decoding relies on maximum a posteriori decoding, which consists in computing the probability that a specific bit was 0 or 1 and selecting the hypothesis with a higher probability. The two main drawbacks of a typical decoding approach are (i) the computational complexity and (ii) the unknown distribution of the channel noise. The classical Viterbi algorithm is used for decoding a bitstream that has been encoded using FEC based on a convolutional code. The Hamming distance is used as a metric for hard-decision Viterbi decoders. The squared Euclidean distance is used as a metric for soft decision decoders. Regarding power consumption, several studies have evaluated the consumption of FPGA as hardware to support LDPC coding [199]–[202]. In the DVB standard with a coding rate of (64800, 29160), the power consumption by LDPC is 12.92W for a throughput of $\sim$4 Gbps, which for a satellite with a maximum power consumption of 50W, the decoding process account for 25.84% of the total of the consumption of the payload for a single reception chain [199]. In the worst case, for small satellites like CubeSatKit, decoding at such a throughput rate is impossible since this task's consumption is larger than the power budget (2W) [200]. In future HTS, where there could be up to thousands of parallel receiving chains on board the regenerative satellite, power consumption is increased with the number of beams up. For example, suppose an HTS satellite has a capacity of 200 beams, each being decoded by a FEC decoding chain with power consumption similar to SmallGEO. In that case, the total power consumption will be proportionally incremented by 200, $\sim$25.8%. Therefore, to overcome these challenges, it is possible to consider a ML approach to learn from data.

c) Proposed ML Solutions: The application of ML to FEC decoding is generally restricted to shortcodes due to the exponential training complexity. For instance, a message with "k" bits gives 2^k possible codewords. Fortunately, the ACM codes of DVB-S2X are generally limited, favouring such a scenario. Two typical decoding approaches based on NN are data-driven and model-driven schemes, as shown in [203]. One of the earliest works on ML for FEC decoding is [204], which showed that the belief propagation decoding algorithm might be equipped with learnable multiplicative weights and trained as a NN to improve error correction performance. Recently, academic works have been published on the topic with the objective of wireless communication receivers, e.g. [205]–[207]. Furthermore, [208] presents a novel approach for decoding 5G data frames (a combined demapper and decoder) based on a combination of autoencoders and DNNs. The performance of the proposed system is compared with traditional implementations based on constellation demapping and LDPC decoders. The proposed approach can obtain a 3 dB gain in SNR, which may be expanded by considering spatial-domain diversity through a MIMO approach. The scheme proposed in [208] may be a candidate for satellite integration in the 5G network.

Key Takeaway 4: Precoding, Link Quality prediction, Predistortion and Coding

The main motivation to apply AI/ML in link quality forecasting is the potential real time response. This would allow a prompt parameters adjusting and a seamless service. NN, and especially LSTM, are the most promising approaches to achieve relatively accurate short-term prediction. To improve the accuracy in the medium/long term new solutions that utilize a priori information have been proposed. There is potential for ML techniques to improve the conventional precoding in SATCOM systems, possibly exploiting the advances made in the terrestrial domain, where model based techniques have been emerging [209]. The ML methods proposed in literature, in fact, require large amounts of data in order to effectively capture the relevant information to estimate the channel matrix. Therefore, hybrid models help achieving a good accuracy while using a smaller amount of training data. Boosting the precoding performance with proper user scheduling (i.e. clustering) is discussed in Section IV-B1 of this survey.

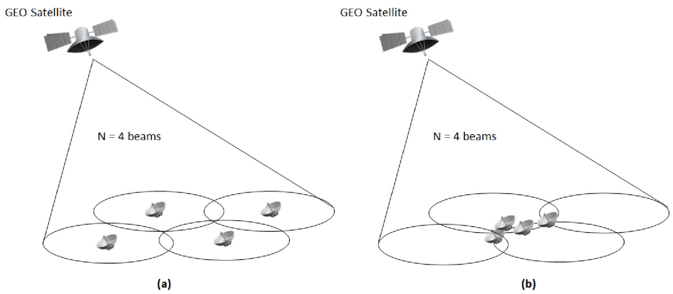


Fig. 11: Unicast Scheduling: (a) Users selected on beam center, (b) Users selected on high-overlapping area

B. Medium Layers

1) User Scheduling:

a) Motivation and Description: Tthe overall system throughput in satellite systems might be strongly limited by interference between adjacent beams. The traditional four-colour frequency reuse scheme helps minimize interference between adjacent cells by using different sets of channels, allowing for efficient use of the available frequency spectrum. However, when non-orthogonal users are scheduled together, even with the four-colour frequency reuse scheme, system performance can degrade due to user interference. This interference can arise due to the non-orthogonal use of frequency resources, which can lead to overlapping signals and reduce the quality of the received signals. Thus, beside the four-colour scheme, advanced interference mitigation techniques at the receiver, e.g., multiuser detection, or the transmitter, i.e., precoding are needed to handle adjacent beam interference.

In recent years, the full frequency reuse scheme has replaced the traditional four-colour frequency reuse scheme. Precoding has been used as an effective co-channel interference mitigation technique to enhance satellite spectral efficiency. Similarly to terrestrial systems [210], [211], multibeam precoding systems are sensitive to user scheduling. Generally, the attainable system rates increase when co-scheduled users have close-to-orthogonal channel vectors. In any case, user data flows are subject to end-to-end delays, frame encapsulation problems and user traffic prioritization, which makes this channel-vector-based scheduling challenging to be deployed in real systems.

Furthermore, the choices on user scheduling (either unicast or multicast) have significant impact when the beam-pattern has overlap and the beams share the same spectral resource. A simple example is drawn in Fig. 11 where the two extreme cases are shown: Fig. 11(a) shows a user scheduling where users in the beam center are selected (thus minimizing the spot-beam overlap and resulting intreference); and Fig. 11(b) shows a user scheduling where users in the beam edge are selected, where the is most beam-pattern overlap (thus where the highest interference is achieved).

b) Conventional Solutions and Issues: Scheduling users in multicast multibeam precoding is a coupled problem. Indeed, the ground station can only compute the precoding matrix once the scheduled users have been determined. To avoid iterative methods, the scheduler has to provide scheduling policies without knowing the resulting attainable rates. In this context, scheduling must involve heuristic approaches that yield to resulting scenarios where users within the same group have similar C/I yet different channel vectors with co-scheduled users served at other beams to attain high data rates. As the line-of-sight component strongly dominates satellite channels, one could resort to latitude and longitude positions to perform the scheduling. This is a substantial complexity reduction of the scheduler as it no longer requires access to reported CSI values. In [212], the authors propose a location-based scheduling algorithm that groups users with similar geographical locations and assigns them to the same beams. An alternative approach is suggested by the authors in [213] who suggest using Euclidean distance to correlate channel vectors and impose channel orthogonality.

Despite geographical scheduling results into the same result as when using perfect CSI in clear sky conditions and perfect satellite feed element frequency precompensation, differences appear when a close-to-real operation is analyzed and fading is considered. In those cases, grouping users considering their Euclidean distance seems to behave well [214] even when mobility is considered [215]. In SATCOM, cellular scheduling can be used to increase the number of users that can be supported and improve system performance. However, as the number of cells increases, the likelihood of co-channel interference also increases. From the authors of [216], it is also possible to avoid interference using graph theory in cellular networks to reduce intercell interferences (ICIs) using the Least Beam Collision (LBC) algorithm. This method avoids the simultaneous scheduling of two adjacent cells that might interfere with each other by refraining from scheduling them simultaneously.

A method to minimize the simultaneous scheduling of users in interference beams is also described in [217]. This method uses partial CSI to avoid scheduling users in interference beams simultaneously. A study in [218] investigates user scheduling for multicast transmissions with full frequency reuse and multicast precoding. Some authors have, however, enhanced their study by using the Euclidean norm and cosine similarity to examine channel characteristics. Also, in [219], the authors sequentially select users with orthogonal channel vectors based on the cosine similarity metric. Consequently, channel orthogonality and semi-orthogonal scheduling, as defined in [210], have been adopted widely by the satellite industry to address scheduling challenges. On a different approach, the authors of [220] use user scheduling to achieve better demand satisfaction by considering both co-channel interference and user demands. Furthermore, considering the joint nature of precoding and user scheduling, the works in [221]–[223] suggest an alternative solution involving suboptimal solutions that approach stationary points.

c) Proposed ML Solutions: Geographical scheduling, explained in the previous subsection, can help simplifying the scheduling decisions, but still relies on drawing arbitraly lines on Earth to define the different geographical sectors of a beam. Fig. 12(a) depicts the conventional way to define the geographical sectors. In recent years, unsupervised ML techniques have been used to automatically group users into clusters with similar characteristics, which helps make the scheduling process more efficient [36]. These clustering techniques can also take into account temporal variations in user traffic, which is particularly beneficial in the context of multibeam satellite systems. In particular, [224] focus on user clustering for multicast precoding in multibeam satellite systems. Two clustering algorithms have been proposed in this context: (a) fixed-size clustering, aimed at minimizing the impact of outlier users, and (b) variable-size clustering based on the K-means++ algorithm. Through numerical simulation, it was shown that the rate achieved with the proposed fixed-size clustering algorithm consistently outperforms the solutions available in the literature, and almost meets the upper bound performance. Also, variable-size clustering is more efficient than existing solutions. However, fixed-size clustering should be preferred when the number of users increases and the channel coefficient similarity increases. Nevertheless, the study does not consider the impact of non-uniform traffic requests on scheduling decisions.

The most accurate user scheduling is achieved when inspecting the channel characteristics of all possible user scheduling combinations. The latter has exponentional complexity with the number of users, and not a valid approach for real-time systems. Geographical scheduling, explained in our original manuscript can help simplifying the scheduling decisions, but still relies on drawing arbitraly lines on Earth to define the different geographical sectors of a beam. Fig. 12(a) depicts the conventional way to define the geographical sectors. However, recent results developed in [225] have shown that ML can be used to optimize the borders of the geographical sectors (see Fig. 12(b)). [225] approaches the user scheduling problem in the context of clustering users as a function of the feature vector of the users, taking into account not only their geographical position but also channel information. Eventually, they evaluate three different algorithms based on UL: K-means (Km), Hierarchical clustering (Hc), and SelfOrganization (SO). Fig. 13, based on our work [226], shows an evaluation of different user scheduling techniques by comparing various unsupervised learning techniques against geographic-based scheduling, evaluating gigabit performance per second (Gbps). The analysis demonstrates a clear advantage of the proposed clustering algorithms regarding efficiency. However, it also notes a decline in spectral efficiency—and thus performance—as the number of multicast users per beam increases, a trend consistent across all evaluated algorithms.

2) NOMA Multiple Access:

a) Motivation and Description: The current SATCOM systems use popular Orthogonal Multiple Access (OMA) schemes such as Time Division Multiple Access (TDMA), FDMA, Code Division Multiple Access (CDMA) and Spaced Division Multiple Access (SDMA), where orthogonal users share time, frequency, code and space, respectively. However, the performance of such OMA schemes is confined by the physical limitations of the resources.

Conversely, in power-domain Non-orthogonal Multiple

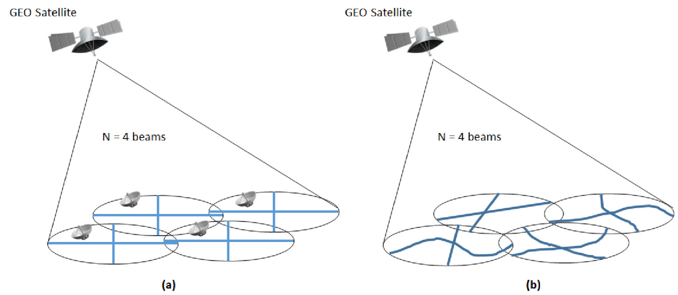


Fig. 12: Geographical Unicast Scheduling: (a) Conventional geographical borders, (b) Geographical borders can be optimized with ML [225]

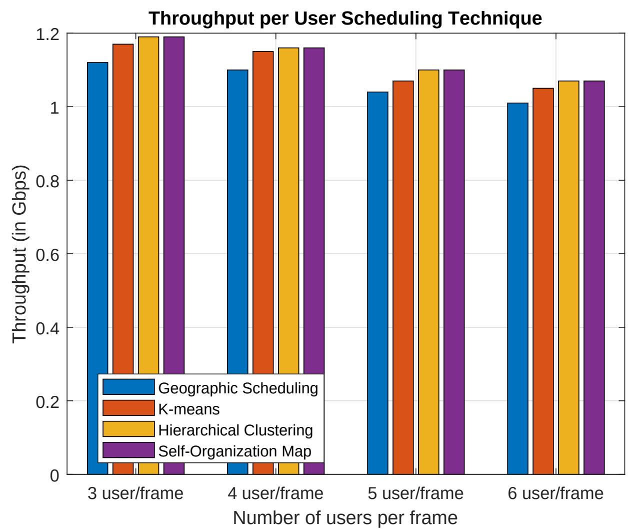


Fig. 13: Comparison between traditional and ML-based techniques for SATCOM User scheduling. The figure presents an evaluation of different user scheduling techniques by comparing various unsupervised learning methods—K-means, Hierarchical Clustering, and Self-Organizing Map—against Geographic Scheduling. The performance is measured in gigabits per second (Gbps) across different numbers of users per frame, ranging from 3 to 6. The analysis shows that the proposed clustering algorithms generally offer higher throughput per user compared to geographic-based scheduling, indicating greater efficiency. However, a decline in spectral efficiency is observed as the number of multicast users per beam increases, a trend consistent across all evaluated algorithms. This underscores the challenge of maintaining high performance with increasing user density.

Access (NOMA), by implementing superposition coding at the transmitter, different users can send their respective signals through the same time-frequency block without interfering with each other. Hence, the concept of NOMA has recently received considerable attention due to its ability to improve power-domain flexibility in managing resources and achieve higher spectral efficiency than OMA. Furthermore, NOMA has numerous advantages over conventional OMA, such as increased spectral efficiency, increased connectivity, reduced transmission latency and signalling costs. Despite such benefits, the resource allocation for satellite-NOMA systems still needs to be fully explored, and many open questions exist.

NOMA introduces transformative capabilities in SATCOM systems, including enabling massive connectivity by allowing multiple users to share the same time-frequency resources, particularly advantageous for Internet of Things (IoT) applications requiring simultaneous device communication. Additionally, NOMA enhances spectral efficiency by serving multiple users concurrently in a single resource block, optimizing bandwidth utilization in SATCOM networks. Moreover, NOMA can cater to latency-sensitive services such as real-time communication by prioritizing critical data packet transmission within the same resource block, ensuring efficient delivery of mission-critical information over satellite links.

b) Conventional Solutions and Issues: Although NOMA offers numerous features that could support next-generation systems, it also has some limitations that must be addressed to utilise its capabilities thoroughly. Compared to OMA, NOMA has greater computational complexity because each user must first decode another user's signal before encoding their own signal. To decompose the overall NOMA signal recovery into distributed low-complexity processes, in [227], a low-complexity receiver has been developed with iterative processing which consists of a linear Minimum Mean-Square Error (MMSE) multi-user detector and a bank of single-user message-passing decoders. Other works have followed similar approaches, such as [228] and [229]. They examine an iterative linear MMSE multi-user detection for both symmetric and asymmetric MIMO-NOMA, and an IRA code is designed for the receiver for asymmetric and symmetric MIMO-NOMA. The authors of [230] formulate a joint network stability and resource allocation optimisation problem to maximise the long-term network utility of NOMA S-IoT downlink system. The authors consider the condition of SIC decoding and propose a practical solution under the Karush–Kuhn–Tucker (KKT) conditions, and then solve the joint resource allocation problem by introducing an optimal solution using the particle swarm optimisation (PSO) algorithm.

In NOMA, the base station should be notified of the channel gains of all users, but doing so will require a significant amount of CSI feedback overhead. To reduce it, [231] propose a scheme where the CSI is acquired only if the BS estimates a high probability of successful UE pairing. [232], [233] study the performance of NOMA with imperfect CSI.

c) Proposed ML Solutions: NOMA enabled SATCOM has brought multiple challenges, which can be addressed using the use of ML techniques. Specifically, the authors of [234] study the DL aided NOMA for resource allocation, power optimization, Channel Assignment and User-Pairing, Data rate Maximization, Signal Detection and Channel State Estimation. Using a DRL algorithm, the authors of [235] study the increased inter-user interference and have developed a dynamic power allocation strategy for NOMA-based S-IoT systems subject to QoS constraints to optimize power allocation factors for NOMA users. The framework utilizes contextual information such as channel quality, data transmission amount, terminal location, and QoS requirements to make online channel and power allocation decisions, adapting to changing environmental conditions without relying on precise channel state information. The output comprises optimized resource allocation strategies balancing success rate, power efficiency, and QoS requirements, with the proposed method demonstrating significant improvements in power efficiency while maintaining QoS guarantees.

According to the authors of [236], a hybrid approach combining data-driven learning and model-based optimization can minimize transmission time in a NOMA-enabled satellite system by optimizing transmit power and terminal time slot scheduling. The framework takes as input a mixed-integer convex programming (MICP) problem formulated to optimize power allocation and timeslot-terminal assignment. The output comprises optimized solutions for terminal-timeslot allocation, which inform subsequent convex optimization processes for power allocation.

Furthermore, NOMA introduces challenges in achieving low AoI due to the interference among users, especially in time-sensitive applications, such as IoT and real-time communications, where verage Age of Information (AoI) is crucial. Accordingly in [237], the authors minimize the average AoI of a NOMA downlink by formulating a MDP problem. Furthermore, to overcome the curse of dimensionality and non-convexity, they propose a DRL-assisted age-optimal power allocation algorithm. In [238], DL was applied to satellite-IoT systems to determine the optimal decoding order for NOMA's SIC process based on an approximation of the implicit mapping between queue size, channel gain, and decoding order. Also, to perform completion time minimization, [239] employ Deep Belief Network (DBN) to solve the joint downlink resource allocation non-convex problem using end-to-end learning. Additionally, [240] proposes the DPO combining learning and optimization to provide a feasible and near-optimal solution. Furthermore, to address the problems introduced by imperfect CSI and channel estimation errors, the Support Vector Machine (SVM) model in [241] showed promising performance by significantly improving user pairing.

3) Rate Splitting:

a) Motivation and Description: Rate-splitting multiple access (RSMA) is an effective multiple access technique that includes SDMA and NOMA as special cases. One extreme case of RSMA is the linearly precoded SDMA scheme which relies on a transmit-side interference cancellation strategy which treats interference as noise. Another extreme case of RSMA is power domain NOMA which uses a receive-side interference cancellation strategy and fully decodes interference [242].

Furthermore, RSMA can benefit from both SDMA and NOMA, and outperforms both in terms of better spectral efficiency, energy efficiency and QoS enhancements with lower computational complexity [243]. The performance of NOMA is more effective with both underloaded and overloaded network loads, along with various channel strengths, perfect/imperfect CSI and channel directions. Thus, RSMA can be described as a computationally simpler bridge between SDMA and NOMA. Additionally, RSMA offers the advantage of controlling computational complexity and data rate by adjusting the ratio for splitting user signals into common and private portions.

RSMA transforms resource allocation in SATCOM systems, offering dynamic allocation of transmission rate among users based on their channel conditions and service needs, ensuring efficient utilization of satellite link capacity. It facilitates adaptive modulation and coding schemes for tailored transmission strategies, optimizing reliability and spectral efficiency for users. RSMA also mitigates interference by allocating orthogonal subchannels, reducing co-channel interference and improving network reliability, particularly in dense user environments.

b) Conventional Solutions and Issues: A comprehensive tutorial of RSMA can be found in [244] that discuss the myths associated with RSMA, along with answers to frequently asked questions about RSMA. Also, [245] discusses open issues of RSMA in Cognitive Radio Networks (CRN), in particular, how to handle mutual interference (functions of the power allocation, rate splitting parameters or the power allocation factors). Thus, both RSMA and CRN parameters (spectrum sharing) must be solved jointly, which leads to a non-convex problem. Furthermore, open issues such as spectrum sensing, physical layer security issues, along with the impact of RSMA on the physical layer and lower MAC layers have been discussed. The authors of [244] discuss the Physical Layer Security issues and state that if encryption is used in higher layers, there will be no privacy or security issues in RSMA.

More specifically to satellite systems, the authors of [246] discuss the Max-Min fairness (MMF) achieved by conventional linear precoding and RSMA in multigroup multicast with imperfect CSI and demonstrate the benefits of RSMA strategies in both underloaded and overloaded scenarios. Also, by combining a modified WMMSE approach with an alternating optimization algorithm, the authors in [247] solve the MMF optimization problem and propose an RSMA approach that is highly promising for multibeam SATCOM systems to handle inter-beam interference, taking into account practical challenges such as CSI uncertainty and practical per-feed constraints. A similar approach is followed in [248], but for Multigateway Multibeam Satellite Systems. Security Analysis was investigated in [249], and a beamforming scheme based on RSMA is proposed to suppress eavesdropping.

c) Proposed ML Solutions: With limited knowledge of channel information and uncertainty of the communication channel, optimizing power allocation in RSMA is very challenging. In the conventional approach, the sum rate maximization of RSMA is generally achieved by the WMMSE algorithm. However, due to high computational complexity, the authors of [250], [251] use a hybrid ML technique based on DL called Deep Unfolding (DU) with momentum accelerated Projection Gradient Descent (PGD) algorithm and outperforms the original WMMSE algorithm in sum rate and speed. In [252], the power allocation problem to common and private streams is discussed. The paper proposes a highly-effective proximal policy optimization based solution, enabling the LEO satellite to learn an optimal power allocation strategy to maximize the sum rate with low computation complexity.

4) Constellation Routing:

a) Motivation and Description: Satellites are usually grouped in a constellation to offer global or near-global coverage and service. Within each constellation, satellites can be connected with the neighbor satellites via inter-satellite links (ISLs) either inter-plane, i.e., the link between two satellites in a different orbit, or intra-plane, i.e., the link between two satellites in the same orbital plane. GEO system has a wide coverage and typically does not require complex routing over the satellite component. On the contrary, MEO and, especially, LEO satellites have a smaller coverage. This brings to a constellation with several satellites and many ISLs between them. As a consequence, efficient routing algorithms are of vital importance to offer global services. The routing algorithm is computed with a fixed transport network once the intermediate nodes receive the commands and traffic flows. However, when the substrate network has a highly dynamic structure, e.g. the NGSO satellite constellations, especially for low altitude orbit ones, and due to the strict power/computational constraints on-board the network nodes, i.e., satellites, the routing has to face numerous challenges. Primarily, with the increase of the nodes and links in the network, the number of available paths and their dynamic behaviour over time increases considerably. This brings more complex routing algorithms to be computed. Secondly, 5G satellite networks are expected to have a multi-layer (LEO-MEO-GEO) structure to provide reliable and ubiquitous connection while accommodating heterogeneous services [253]. the heterogeneity of on-board capabilities between the GEO-MEO-LEO satellites and the difference in the link latencies additionally increases the complexity of the algorithms since the number of constraints grows.

To handle this increasing complexity and challenges in the intra-layer, AI/ML techniques have been introduced.

In the following sections, we will describe the above mentioned challenges, together with the proposed AI/ML techniques to overcome them.

b) Conventional Solutions and Issues: First, a valuable routing algorithm should guarantee each application's required QoS, e.g. latency, packet loss, and data rate. To handle this together with seamless handovers, due to the mobility of the substrate network, a temporal subdivision into time intervals is applied such that the substrate network is considered static within each time interval. Then, traditionally, the most common approach to solve the routing is the shortest-path (SP) [254].

While SP was efficient with the first generation of MEO and LEO constellations, several issues were raised with the advent of more complex and more extensive networks. Alternative conventional solutions such as the minimum hop count [255] has also been proposed for Mega-Constellations. However, due to the high mobility of the Space-Air-Ground Integrated Network (SAGIN) nodes, i.e., satellites, flying devices and mobile users, and the high volumes of data which may easily congest the channel [256], providing seamless transitions remains challenging. Additionally, as highlighted in [257], the routing problem along the SAGIN not only deals with the link capacity constraints but also needs to consider the different caching and computing capabilities of satellites, which increases the overall computational complexity.

c) Proposed ML Solutions: Authors in [258] describe a CNN based routing algorithm to optimize the SAGIN's performance via traffic patterns and the remaining buffer size of GEO and MEO satellites. They propose online training, distributed over multiple satellites, due to a high volume of data, and does not interrupt the throughput while training.

Authors in [257] propose a Deep Q-learning (DQL) approach to overcome the computational complexity of a joint optimization routing algorithm. The DQL algorithm is described with 1) the state space, function of user-LEO angle, networking, caching and computing states, 2) the action space and 3) the reward function, defined as the efficiency of unit resource. In [259], authors propose a DRL algorithm where the rational agent of the model learns following the replays and selects the route with the smallest Round Trip time (RTT). The routes are chosen, although in principle, crossing more nodes, and therefore longer, in the end, have better effectiveness and a lower load on the bottleneck router.

5) IoT Channel Access to Scheduling:

a) Motivation and Description: IoT via satellite is envisioned as a viable solution to connect devices in remote places due to the ubiquitous nature of satellite coverage, and thus dramatically complements terrestrial IoT solutions. However, due to the massive number of terminals, using optimal resource access and allocation policies would result in a computational load incompatible with the processing constraint of IoT devices. On the other hand, using simple access techniques such as random access lead to under-utilization of the network resources. Hence, ML is an interesting solution to offer a trade-off between channel utilization and computation complexity. As presented in [7, pp. 92], access methods can be grouped in two categories: fixed assignment (FA) based, and random access (RA) based. The former ensures contention-free access but requires precise synchronization, while the latter has little synchronization constraints but has to deal with packet collision probabilities. In the following paragraphs, we will separate FA and RA-based solutions with different constraints, challenges, and network and IoT device designs.

b) Conventional Solutions and Issues: Two of the best known FA solutions are the NTN narrow band IoT (NB-IoT) [261] and 5G New Radio (NR) standards. Both are part of the 5G cellular access technology developed by the 3GPP. The fact that those solutions are part of a cellular standard is a strength and a weakness. On the one hand, it allows for the seamless integration of NTN into other cellular networks. On the other hand, those standards impose restrictions that do not necessarily mix well with the constraints found in NTN. An issue is the higher RTT delay, especially in GEO links. In LEO systems, other common issues are differential Doppler and high demand variability due to short orbital periods. These issues can conflict with the precise synchronization needs of Orthogonal Frequency-Division Multiple Access (OFDMA), and lead to more complex and expensive terminal design (e.g. by including GNSS receivers). Most of the existing literature focuses on finding solutions that solve those issues with as few modifications as possible to existing standards.

RA solutions are well suited for satellite Machine-to-machine (M2M) communications as they satisfy most of the criteria inherent to this type of communication. The authors of [262] provide a survey on RA solutions for satellite uplinks, focusing on M2M communications. Originally based on the ALOHA protocol, RA methods were first used in SATCOM for capacity requests [263]. Successive improvements, such as in [264], have allowed new RA methods to achieve low ($< 10^{-3}$) Packet Loss Probability (PLR) even at high (≥ 1) network loads, enabling applications in massive machine-type communications (mMTC). However, the very high number of terminals, and thus access requests, coupled with the constraints of NTN networks (e.g. high RTT), brings down the performances of those solutions in satellite IoT networks.

c) Proposed ML Solutions: As for the conventional solutions, we will present the FA ML solutions first. The authors of [38] presented how classical DAMA with RA requests could be improved with dynamic channel allocation and DRL, retaining the high efficiency of FA while adding the flexibility of RA. The optimization is done on the satellite side, which receives transmission requests from the terminals and schedules the data transmission up to a given number of time slots ahead. The bandwidth, the transmission completion time, and the number of scheduled transmissions for each time slot characterize the

TABLE X: Summary of works on improving the performance of SATCOM medium layer use cases with ML. DBN is acronym for Deep Belief Network

Medium Layers				
Area	Ref	Application	ML approach	ML Improvement
User Scheduling	[36]	users clustering,congestion prediction	DBSCAN, k-mean, hierarchical	increased rate
	[224] , [225]	users clustering	K-mean, hierarchical	increased rate
NOMA Multiple Access	[234]	NOMA survey	different ML	/
	[236]	NOMA-Enabled Satellite Systems	Dual-DNN , Hybrid ML	lower complexity
	[237]	NOMA Satellite IoT	DRL	Low Age of Info
	[239]	Multi-Carrier NOMA	DBN	Lower Power
Rate Splitting	[250], [251]		Deep Unfolding	sum rate speed
	[252]	power allocation problem to common and private streams	DRL	sum rate at lower complexity
Constellation Routing	[258]	Satellite-Terrestrial Networks	CNN	Overall Performance
	[257]	Software-Defined Satellite-Terrestrial Networks	DQL	Overall Performance
	[259]	satellite Mega-Constellations	DRL	Latency
IoT Channel Access to Scheduling	[38] , [137]	Satellite IoT-Fixed Assignment	DRL	reduced energy consumption
	[59]	Random Access Channel in IoT LEO networks	Deep Dyna-Q Learning	Overall Performance
	[260]	IoT satellite terrestrial relays network	model-free Q-learning	Increased Throughput
	[235], [238]	NOMA Satellite IoT	DQN-based DRL, DNN	higher capacity, improved arriving rate, and queuing delay

states. The reward function increases when the sum of transmission completion time decreases. The authors also present several techniques to speed up training sessions. The results showed that channel access DRL (CA-DRL) reduces by up to 87% the delay in request satisfaction compared to first-come-first-served and pure ALOHA policies. However, no comparison is offered against more advanced techniques like CRDSA. This work was expanded by the same authors in [137]. The authors added multibeam, QoS satisfaction, and energy efficiency, extending terminals' lifetime in remote IoT networks. The authors formulate a MDP for allocating tasks, defined by their size and location, to channels and beams. They show how to use DRL to solve this problem. The action space is defined as all possible channel allocations. To reduce its size, the allocation of a channel to a beam is done sequentially. The reward is a trade-off between two components: the first represents power management. In contrast, the second represents QoS satisfaction as a service blocking rate within the time window. The authors also construct the user requests into an image as the input of the considered NN, which can reduce the input size and accelerate the learning process. The results show a reduction in energy consumption of up to 67% compared to random and greedy algorithms and minimize the service blocking rate among all algorithms.

Regarding RA ML solutions, the authors of [59] have presented a Deep Dyna-Q Learning solution for the random access control in IoT LEO networks (slotted ALOHA). IoT devices connect via random access opportunities, of which the product of preambles and physical random access channels available determines the number. The authors present an optimization problem to maximize the utilization of idle RAOs while keeping the transmission delay under a given threshold. An enhanced access barring (EAB) mechanism is used in the case of congestion. The states in the MDP are defined as the number of devices connecting to each satellite. The action set is the number of available RAO (discrete set). The reward takes values in the set {1,0,-1}, depending on whether the utilization in the next step is, respectively, higher, equal, or lower than the current one. Probabilities of transition between states are expressed analytically based on the Poisson process for both contention-based and contention-free random access. The authors then present a solution to the optimization problem in the form of a Deep Dyna-Q Learning algorithm and a model-free Deep Q-learning algorithm for comparison. Both Q-learning algorithms present a 3.5-fold improvement in access efficiency over classical dynamic RAO allocation. The proposed Deep Dyna-Q Learning solution performs similarly to the model-free Deep Q-learning. It does not necessitate the feedback interactions between satellites and IoT devices needed in model-free solutions.

As shown in the previous section, the NOMA technique has been applied with ML in several works, to improve the efficiency of SATCOM systems. Works [237], [235] and [238] presented in IV-B2 utilize DRL techniques for AoI, power allocation and Successive Interference Cancellation (SIC) decoding for NOMA downlink system in satellite IoT networks.

The authors of [260] have applied a model-free Q-learning algorithm in the context of IoT satellite terrestrial relays network (STRN) with NOMA. This work is a combination of [265] and [266]. In this scenario, the IoT devices communicate with a nearby terrestrial relay, which then transmits the aggregated data to satellites. The terrestrial relays are assumed to perform SIC based on the power imbalance between received signals. Each IoT device is a learning agent. The states are defined as the timeslots, while the actions are defined as the channel's choice. The reward comes from a single feedback bit transmitted by the relay to the device and is either one if the transmission is successful or minus one if it is not. The Q-learning algorithm replaces the random time slot and channel selection by learning based on the relay's feedback. Results show up to an 18% improvement in spectral efficiency over SA-NOMA. In this context, Yan et al. Literature [267] presents a resource allocation for IoRT with joint time-variant channel fading process and stochastically fluctuating solar infeed process. The solution is based on SARSA based actor-critic RL and is evaluated in average amount of downloaded IoRT data by the satellite. The authors conclude that performances depend on battery capacity.

Key Takeaway 5: Medium Layers

Most of the rate splitting, constellation routing and IoT channel access solutions are RL based. Given their trial and error nature, RL techniques are suitable for highly dynamic radio channels as in SATCOM. In addition, optimizing a network routing strategy dynamically is a promising strategy to diminish the latency. The agent in the RL solutions proposed is usually placed on the satellite, and the algorithm is supposed to be run onboard. However, this approach is only sometimes a good choice for all scenarios. The satellite computation requirement in this distributed architecture is much higher due to the onboard training. However, the current research works do not offer an overview of the demanded computational power to run the proposed RL algorithm.

C. Upper Layers

1) Traffic/Congestion Prediction:

a) Description and Motivation: Satellite networks are evolving towards multilayer systems that integrate different satellite constellations to improve performance and enable new use cases [268]. These multilayer networks, consisting of satellites at different orbital altitudes, offer advantages such as wider coverage and lower propagation delay [37]. However, ensuring fair and efficient utilization of network resources in these networks requires intelligent routing control and smart resource management to handle traffic load according to QoS requirements [36]. Predicting and managing network congestion is crucial for effective traffic load balancing and resource allocation.

Monitoring incoming traffic rates is a common method to detect network congestion. However, simply balancing the load may not be sufficient to effectively prevent congestion. Therefore, congestion prediction mechanisms are necessary to distribute traffic among available network resources and proactively manage congestion. These prediction mechanisms play a crucial role in network management, design, resource allocation, traffic routing, and anomaly detection [37].

b) Conventional Solutions and Issues: In the context of satellite networks, the problem of load balancing and congestion prediction has been addressed through various approaches. One study proposed a hybrid GEO/LEO satellite network that leverages interlayer interconnections and congestion prediction to distribute traffic effectively [44]. The scheme defined normal and warning states for satellites based on congestion probabilities. Satellites in the normal state monitor traffic rates, while those in the warning state perform traffic distribution and information exchange for congestion prediction. Although this scheme showed effectiveness through simulations, it relied on predefined congestion thresholds and did not consider the use of ML techniques.

c) Proposed ML Solutions: ML techniques have been used to improve traffic congestion prediction in satellite networks. An approach proposed a link congestion prediction method using ML algorithms, such as CNNs [269]. The authors designed a software-defined network model and collected state information of switches and links to train and test the ML algorithm. The CNN model achieved high prediction performance, reaching 98.3%.

Other ML models, including CNNs, LSTM, and Fully Connected DNNs, have also been used for network traffic prediction [34]. However, these models did not explicitly consider the topological information of the network, resulting in lower prediction performance. To address this limitation, a Diffusion Convolution Recurrent Neural Network (DCRNN) was proposed, which captures critical topological properties of the network and improves traffic prediction accuracy [270].

2) Integrated Satellite-Terrestrial Networks:

a) Motivation and Description: Since 3GPP Release 15 [285], as the satellite and terrestrial networks share common objectives, satellite networks are now part of 5G and are referenced as NTNs within the standard. Terrestrial networks expect to benefit from the wide coverage area of satellites, which does not require deploying any terrestrial infrastructure to extend their coverage. This integration should bring more flexibility and efficiency in network deployment and management. However, this integration is challenging as both networks have specificities and must converge technologically. To achieve this objective, the network slicing paradigm can be used [286]. A network operator can create end-to-end partitions and deploy services while guaranteeing their end-to-end Key Performance Indicators (KPIs).

Various research projects have focused on the integration of satellite networks into terrestrial mobile networks. We can cite the VITAL project, which aimed to apply the concepts of Software Defined Networks (SDNs) and Network Function Virtualizations (NFVs) to the satellite network [288] in order to increase its flexibility and allow close integration with 4G networks. It was followed by the SaT5G project [289], which studied the integration of satellites in 5G networks. The table XII summarizes the different modes of satellite integration into 5G networks: direct access modes ,

TABLE XI: Summary of works on improving the performance of SATCOM upper layer use cases with ML. TL is acronym for transfer learning, ML for Meta learning, DCRNN for Diffusion Convolution Recurrent Neural Network

Upper Layers				
Area	Ref	Application	ML approach	ML Improvement
Traffic Prediction	[269], [34]	congested SATCOM	CNN, LSTM, Fully Connected NN	improved accuracy
	[270]	congested SATCOM	DCRNN	improved accuracy, network topology properties
Integrated Satellite-Terrestrial Networks	[271]	network slicing over integrated 5G-satellite networks	TL, ML, and RL	better dynamic traffic demand management
	[272]	network slicing over integrated 5G-satellite networks	RL	increased user acceptance ratio
	[273]	resource allocation in integrated 5G-satellite networks	NN	decreased latency
Edge Computing	[257]	SAGIN routing and caching	deep Q-learning	Overall Performance
	[64] , [49]	IoT adn SAGIN	RL, DNN	Lower Complexity and Cost, Computational time
	[274], [275]	distributed system	caching	Coverage, User Rate
Device Authentication	[276], [277], [278]	Spoofing Attacks	SVM, random forest, k neighbor	classification accuracy
	[279]–[281]	Antenna fingerprinting	DNN, RNN	accuracy
Quantum Key Distribution	[282]	quantum communication networks	LSTM	QBER, TX efficiency
	[283]	moving platforms	NN	computational power
	[284]	quantum communication networks	Random Forest	efficiency

TABLE XII: Satellite-Terrestrial Integration Modes [287]

Integration type	Challenges
3GPP Access	Support of the NR waveform within the satellite
Trusted non-3GPP Access	Integration of the satellite in trusted non-3GPP Access mode within the standard
Untrusted non-3GPP Access	Support for 3GPP untrusted access mechanisms within the satellite network
Relay node with 3GPP Access	Support of the NR waveform within the satellite, adaptation of the relay mechanism within the satellite terminal
Relay node with Trusted non-3GPP Access	Integration of the satellite in trusted non-3GPP Access mode within the standard, adaptation of the relay mechanism within the satellite terminal
Relay node with Untrusted non-3GPP Access	Support of 3GPP untrusted access mechanisms within the satellite network, adaptation of relay mechanisms within the satellite terminal
Transport Network based on 3GPP System specification	Definition of a satellite system compatible with the 5G standard
Transport Network non-based on 3GPP System specification	Define an adaptation layer for the satellite network considered as a transport network

indirect access modes as a relay node (using gateways to connect other, smaller User Equipments (UEs)), and integration as a Transport Networks (TNs) for backhaul link services. Following these projects, Zhu et al. [25] listed all challenges regarding the 6G-satellite integration. Depending on the integration scheme, adaptions have to be achieved at various layers of the systems. Interconnection and integration should take place at the orchestration plane, control plane and data plane. This also implies comprehensively allocating and efficiently managing terrestrial and satellite components' resources. A complete integration scheme is direct access where Satellite Terminals (STs) embeds all the 5G protocol stack and connects directly to satellites also compliant with 5G Radio Access Network (RAN). This method is also the most complex, as satellite networks need to be fully 3GPP compliant. Then, depending on the trusted mode, the relay node can be an intermediate solution where the ST relays (with or without embedding the 5G protocols) all data from UEs to the RAN. The last and easiest mean to realize such integration is to consider the satellite network as a transport network for the 5G system and create backhaul links between 5G RANs and Core Networks (CNs). Considerable research was conducted using conventional or ML solutions.

b) Conventional Solutions and Issues: Ahmed et al. [290] have worked on the integration of satellite and 5G using SDN/NFV and proposed a method for the reservation of hybrid resources in terrestrial and satellite Point of Presences (PoPs) using Mixed-Integer Linear Programming (MILP) combined with an online algorithm to ensure a minimum end-to-end delay. Drif et al. [291] have analyzed the network slicing paradigm and applied it to satellite networks to enhance its flexibility and integrate it as a network slicing within 5G networks. They have listed all the challenges related to slicing in satellites, identified interconnection points between terrestrial and satellite networks and produced a novel architecture to mutualize all satellite resources into a single physical infrastructure. They have implemented their work on a 5G and satellite network in [292] and demonstrate the end-to-end service and QoS continuity using network slicing. Kodheli et al. have listed the challenges of using 5G direct access in LEO mega-constellation and proposed high-level solutions in [293] regarding the Random Access procedure. The authors pursued their research in [294], where they have detailed all the current limitations of using mobile network protocols in GEO NTNs. They have proposed solutions to push these boundaries and validated them on a physical testbed using a channel emulator and a 4G modified stack of the OpenAirInterface (OAI) software.

c) Proposed ML Solutions: Lei al. [271] have presented AI-based solutions to manage network slices deployed over the integrated 5G-satellite networks. They have listed major issues of applying AI in such networks and proposed solutions to two distinct dynamic scenarios: predictable network variation using Time-expanded Graph (TEG) and unpredictable network variation (e.g., sudden change in mega-constellation topologies), which requires fast adaption mechanisms due to model drift. Solutions can be conventional learning (retraining a model), transfer learning, Meta-learning, or RL. Rodrigues et al. [272] proposed combining network slicing with ML to optimize links in combined 6G-satellite networks. Their ranking-based framework shows an increased user acceptance ratio compared to the traditional methods. Similarly, Bisio et al. in [273] have developed a solution mixing queuing theory and neural network (NN) to minimize this time latencies in end-to-end 5G-SATCOMs.

3) Edge Computing and Caching:

a) Motivation and Description: Edge computing was introduced to avoid computing and storage capabilities being concentrated in centralized locations and most likely far, in terms of network topology, from the network user devices. In fact, on the opposite, the edge computing paradigm runs applications and services in hosting servers/hardware close to the user devices. The premise of edge caching is to prefetch popular contents at the edge caches close to end users, thus, when the users request the cached contents, they can be served immediately without transmission from the data server through the core networks. Satellites, due to their ubiquitous coverage and low latency, when considering LEO satellites, can strongly support terrestrial networks to apply the edge computing paradigm. Edge computing is typically used in SATCOM in two main solutions. Computation offloading [295], whether total or partial, is the technique to offload computational tasks from the cloud to the local Mobile Edge Computing (MEC) servers. This is a flexible approach, depending on the QoS application/user requirements, e.g. tolerated latency and power constraints, the computational tasks are offloaded to servers accordingly. For instance, delay-sensitive applications are expected to be partially offloaded to servers due to time constraints.

Content caching is the second common technique for edge computing over SATCOM [296]. The lack of spectrum availability has forced to find new solutions to minimize the traffic over information networks. Caching the contents to servers/stations close to the user, reduces the transmissions over the network and the overall latency experienced by each user.

b) Conventional Solutions and Issues: Conventional caching is to exploit the long-term content popularity to determine that cached content. In general, based on the history of requested data, the most popular contents will be prefetched to the cache [297]. In [298], several techniques are proposed to decide the location to which tasks should be offloaded. Authors propose different scenarios where tasks are either offloaded to close terrestrial servers, on-board of satellites or close to ground stations.

One of the issue/challenge, presented in [49], when implementing edge computing over SATCOM, is the high dynamicity of the network. Due to fast and frequent variations, the channel features and devices availability is critically unstable and time-dependent. This might bring to delay or failures when communicating to the required servers. In addition, as the beyond 5G SATCOM networks are expected to be very heterogeneous, especially in terms of on-board available resources, the optimization design of the offload policies should be properly analyzed, considering the variety of available on-board capabilities/resources.

c) Proposed ML Solutions and Lesson Learned: The majority of proposed ML solution for edge computing in the literature are developed for terrestrial networks. However, recently few contributions have emerged in the area of integrated satellite-terrestrial networks. Authors in [257] propose a deep Q-learning approach to solve the joint optimization of routing and caching for SAGIN. ML-based edge computing is mainly proposed for IoT scenarios, because the highly dynamic and random computing task arrival makes the edge computing deployment challenging. A similar scenario is considered in [49], where authors work on the optimization of computational task offloading for IoT-based SAGIN networks. In this context, they propose a RL approach to learn the timely network behaviors in order to determine the optimal offloading policy. The learning process is improved by the use of DNNs, policy gradient and actor-critic methods. The final objective is to minimize a composite function of delay, energy consumption and server usage cost.

The application of SATCOMs due to high bandwidth and wide area coverage is investigated in feeding several network caches at the same time using broad/multi-cast [274], [275]. The work of [274] uses the satellite broad/multi-cast to feed the caches at the user side. The authors of [275] consider a network comprised of proxy servers with individual cache storages. If the requested content is not available in the cache, it is routed to the gateway for satellite transmission. Based on the number of requests, the file size, and the available satellite bandwidth the request will be admitted or dropped. The satellite multicasts the requested content and the global popularity. Each server uses the local and global file popularity to update the cache. While [275] proposes satellite multicast in cache feeding, it does not consider the backhaul cost, user link, cache storage limit, handling the dropped packets at the gateway, and the interaction between the macrocell and SBSs.

4) Network Security-Device Authentication:

a) Motivation and Description: Satellite Communication Systems (SCSs) can be an attractive target for attackers due to their importance in global communication systems. Thus, a hacker can launch cyber-attacks at scale by targeting a few key components that constitute the backbone of the global SCS. The risk of attacks on SCS is further aggravated due to a wide threat surface caused by the ease of spoofing wireless devices and limited on-board computing power, which prohibits the implementation of complex cryptographic techniques [299]–[301]. One of the most common attacks in this context is spoofing where a hacker impersonates a legitimate device in the network to provide tampered or falsified information to the network users [300]. These attacks put SCSs on a high risk of service outage, ransomware attacks, and even political and financial losses [302]. With the advent of distributed learning techniques, e.g., Federated Learning (FL), device authentication becomes vital to deter various attack vectors including model and data poisoning, membership inference, and reconstruction attacks by the unauthorized agents [303].

b) Conventional Solutions and Issues: Traditional approaches for device authentication may be based on Secret-key Cryptosystem (SKC) [304] or Public-key Cryptosystem (PKC) [305]. The server maintaining the secret-key tables in SKC-based authentication schemes become an attractive target. On the other hand, high complexity of PKC-based schemes is a major challenge for their use in low-powered devices. Some other issues in these approaches include high transmission delays and session dependence, i.e., if the key of a session is compromised the entire subsequent communication and authentication is compromised. Recent approaches for device authentication include blockchain [306], orbit-based authentication using time-difference of arrival [307], and hierarchical group key distribution [308]. Some common demerits of these traditional approaches include model dependence, low reliability, and low cost efficiency due to an increasing number of network nodes.

c) Proposed ML Solutions: In the recent years, intelligence-based approaches for authentication have emerged providing cost efficiency, high reliability, and a fairly high level of model independence [309]. Another major advantage of ML-based approaches is the departure from session-based authentication to the continuous protection throughout the duration of communication.

In [278] and [276], authors proposed a supervised ML approach for detecting Global Navigation Satellite System (GNSS) spoofing signals. The authors used code, phase, doppler, and signal strength measurements in different frequency bands as data features sampled at 1Hz. The spoofing was performed as an intermediate timing attack aimed to affect the receiver's clock divergence by emulating a satellite clock drift. The specific algorithm utilized in this approach was SVM, which resulted in a high accuracy of more than 98.5% for different datasets.

The authors of [277] investigated similar spoofing attacks on GNSS. They compared the performance of multiple ML methods, namely, SVM with radial basis function, k-nearest neighbors, adaptive boosting (AdaBoost), decision tree, and random forest. They found that the simple classification based on decision tree outperformed other methods in their considered scenario providing high accuracy with a very low false-alarm ratio.

ML-assisted antenna fingerprinting is another attractive approach for authenticating the wireless communication devices. This approach exploits the antenna manufacturing defects that are unique to each antenna and cause identifiable waveform imperfections [279]–[281]. One major challenge in antenna fingerprinting is degradation of antenna due to different environmental factors that might alter the antenna fingerprint [310]. The authors of [311] used a RNN to capture temporal variations and provide robust antenna fingerprinting of different LEO scenarios with a high accuracy of 99.34% for 198 days despite antenna degradation.

5) Network Security-Quantum Key:

a) Motivation and Description: The wide coverage and broadcasting nature of satellite signals make them susceptible to eavesdropping and information leakage to malicious parties [312], [313]. Data security protocols aim to eliminate the possibility of information leakage to eavesdroppers. Two main approaches to ensure data security are 1) physical-layer security (PLS) and 2) data encryption in higher layers [314], [315].

PLS methods operate under the premise that the wiretap channel to the eavesdropper is inferior to that of the intended receiver. To this end, the randomness and time-varying nature of wireless channels are exploited [316], [317]. New techniques are being developed that utilize multiuser MIMO channels to ensure that eavesdropper ends up with a worse channel than the intended users due to interference [318], [319]. On the other hand, data encryption in higher layer relies on a secret key shared between transmitter and receiver to encrypt data. Data encryption in higher layers can be preferred over PLS due to its modular nature and independence from operating/channel conditions. However, the biggest demerit of data encryption techniques is that they can be compromised if an eavesdropper has strong computational powers or a reasonably big quantum computer [312], [320].

b) Conventional Solutions and Issues: The advent of quantum key distribution (QKD) methods has eliminated the biggest demerit of key-based encryption by providing unconditionally secure keys that can ensure information-theoretic security [321]–[329].

In the context of SATCOM, QKD methods become more attractive due to a unique symbiotic relation between the two. That is, not only QKD enables to achieve information-theoretic security of SATCOM but also SCSs have a vital role in achieving global-scale QKD [330], [331].

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

To demonstrate the approach feasibility, the work in [332] presents the configurable finite-size secret key rates that protocols with continuous variable QKD may achieve for both downlink and uplink. QKD systems are very sensitive to the environmental factors, e.g., phase drift caused by internal as well as external factors, channel noise, and photon losses. Satellite channels can have high variability in these factors due to weather, satellite mobility, and imperfect internal devices. Accurate prediction and tracking of these factors is crucial to maintaining correct operation of QKD systems. Traditional approaches for tracking the relevant parameters perform a scan before transmission, which amounts to a significant "down-time" for calibration of QKD equipment [282], [333].

c) Proposed ML Solutions: The authors of [282] employed LSTM network to predict relevant physical parameters in real-time and actively control QKD devices to ensure a stable operation over the course of 10 days. The performance of resulting system was comparable to that of traditional "scanning-and-transmitting" schemes in terms of quantum-bit error rates and key transmission rates. Lack of down-time for scanning resulted in a high system efficiency over the course of continuous operation. The authors of [283] targeted the QKD over free space on moving platforms including satellites. They employed a NN to predict optimal parameters for operation of QKD in variable environments. The resulting system required low computational power in its operation and was demonstrated on hardware devices including Raspberry Pi 3 and a mobile phone consuming less than 5 W. Compared to a brute force search for the optimal parameters, the proposed approach provided up to two to four orders of magnitude speedup while providing a 95% to 99% of the optimal secure key rate for a given protocol.

ML was employed in [284] for real-time selection of optimal QKD protocol in a given environment characterized by dark count rate, efficiency of single photon detectors, misalignment error rate, and transmission distance. The authors employed random forest and compared it with other approaches e.g., support vector machine, K-nearest neighbors algorithm, and CNN. Testing results showed an accuracy of over 98% for selecting the most optimal QKD protocol in a given scenario by random forests.

Carrier recovery is another critical task in modern continuous-variable QKD systems. The authors of [334] employed an unscented Kalman filter for carrier recovery in noise over a 20 km fibre-optic link. The experimental results showed low variance and high stability in excess noise even at low pilot powers.

Key Takeaway 6: Upper Layers

Lessons learned from the traffic prediction ML solutions include the importance of considering network topology for accurate traffic prediction and the potential of ML techniques, such as CNNs and LSTMs, in achieving accurate congestion predictions for specific time windows. These ML models provide insights into future congestion levels and enable proactive congestion management in satellite networks. Moreover, the improvement of traffic prediction ML solutions is evident when used with clustering approaches. Given that congestions prediction tasks might be run daily, a robust data cleaning and preparation is vital to prevent gaps in the dataset.

As shown in X and XIII, the proposed ML techniques for the upper Layers show a variety of various ML architectures as well as different training methods. Most current research, however, is focused on integrating with the current terrestrial networks and needs to consider future SAGIN, where mobility will add complexity and play an essential role in the network performance. Currently, there are some deployed ML testbeds explicitly designed for satellite networks. Moreover, O-RAN is envisioned to unleash the great potential of AI in enabling the future 6G networks via satellite-based NTNs by addressing various associated challenges. Nevertheless, both O-RAN and NTN standardization aspects are still in development, and different SDR-based 5G protocol stacks, such as OAI, are being incorporated with NTN adaptations. In addition, the presented works show a trade-off AI-enabled SAGIN between resource allocation and AI cost and other costs, such as using clouds/edge computing to increase the available computational resources for AI but at the expense of raising the overall budget and security concerns.

Both centralized [258] and decentralized [49] architectures have been proposed, with online and offline training. However, the inherent limitations of both architectures at this early stage pose obstacles for a proper evaluation and more varied scenarios (latency tolerant/mission critical) need to be further investigated.

The ML-assisted physical layer authentication methods complement the device authentication employed at higher layers. Highly reliable and model-free gate-keeping against spoofing and impersonation attacks at the physical layer greatly reduces the number of possible attacks that can be carried out at the higher layers. This makes satellite systems more reliable and difficult for malicious agents to intrude.

The ML-based operations and optimization of QKD systems demonstrate a high potential of ML in achieving a global-scale QKD network. Considering the highly variable nature of SATCOM channels, it is clear that ML-based solutions provide an efficient solution for system-parameter tracking and prediction, which in turn achieves optimal performance of QKD that is an important component for realizing the goal of unconditionally secure global-scale communication over SCSs.

D. Outlook

1) Cooperative Satellite Communications:

a) Motivation and Description: Cooperative SATCOM is integral to satellite-based applications like remote sensing, surveillance, joint communication, joint scheduling, distributed beamforming, and sensing [335]. Specifically for LEO satellite networks, implementing cooperative communications becomes challenging due to their high

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

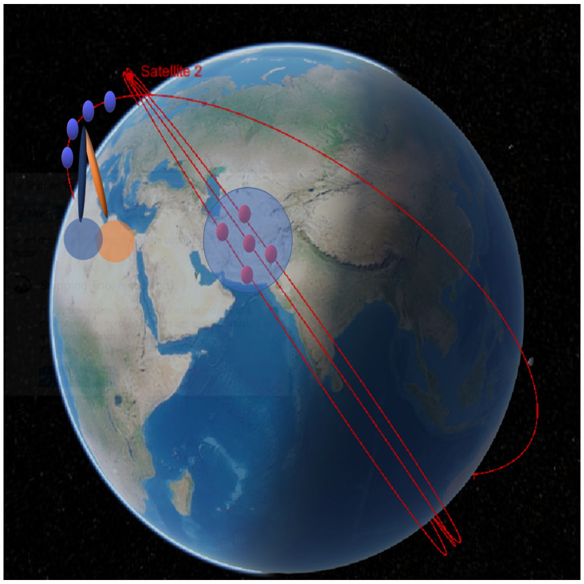


Fig. 14: Distributed beamforming using satellite constellation.

mobility. The existing cooperative satellite-based communication requires a huge amount of communication among satellites for cooperative tasks. This creates problems in establishing joint beamforming, joint scheduling, and other cooperative satellite applications in real-time [336]. In the current scenario, the LEO SATCOM networks such as SpaceX, and OneWeb are gaining popularity because of their low latency, seamless connectivity and broad coverage [337]. However, the networking of these small satellites considers different factors for successful cooperative communication. One crucial factor is the distributed processing and synchronization of satellite networks for coordinated applications [338]. Distributed processing refers to the decentralization of the computing processors, which are physically separated. This distributed processing is application specific. Additionally, these distributed processors can have different structural architectures. It is essential to have efficient distributed processing for effective cooperative satellite-based communication. A pictorial representation of the distributed beamforming performed by a satellite constellation is shown in Figure 14.

b) Conventional Solutions and Issues: The distributed processing in cooperative SATCOM exists in different architectures, namely a Star, a Link, Linear, Hybrid and Layered architectures [339]. These existing architectures pose challenges for distributed processing in terms of power, volume, weight, and size constraints of satellite platforms [340]. However, the main issue lies in the non-optimal utilization of the parameters. This allows employing model compression schemes by removing redundancy or adapting to a compact design with high accuracy using neural architecture search [340].

c) Proposed ML Solutions: The architectural optimization of the NN is termed Neural Architecture Search (NAS) [48]. The NAS is an efficient tool to optimize the hardware architecture for distributed processing in satellite on-board processing while keeping the constraints of power, volume, weight and size [340]. It works on a reward and learning model to generate high-performance architecture. The NAS generated architectures are observed as faster, more accurate, less complex, and less expensive than conventional schemes like gradient descent, evolutionary algorithm, and RL [341].

2) Ground Segment Dimensioning:

a) Motivation and Description: The ground segment is that part of a SATCOM system that employs a variety of node designs and network configurations to provide and manage services delivered, on the one hand, to end-users and, on the other hand, to satellites using feeder links. Service to the ground segment (GS) of an NGSO system depends largely on the nature of the link, which is shorter but more dynamic than its GEO counterpart.

The GS dimensioning (GSD) includes determining the number of GWs needed, the antenna parameterization, the traffic model, and the switching strategies between backup GW [342], [343]. The location of the gateways is one key requirement and vital in NGSO constellations due to the high number of elements that make up the constellations. The location of these elements is strategic for properly functioning these constellations' new services. This strategy can be dynamic as a function of the weather conditions, considering services with greater security restrictions, such as government services and political conditions.

b) Conventional Solutions and Issues: [344] compares GS architectures for constellations using feeder links in Q/V-band against those using E-band. In addition, a method is developed to determine the locations of the minimum number of ground stations that maximize the system capacity while achieving desired QoS levels. The work in [345] analyzed the handover performance in a LEO-based Non-Terrestrial Network (LEO-NTN) via system-level simulations, focusing on ground-segment optimization by traditional methods. Two algorithms for dimensioning the optical ground station (OGS) network with MEO satellites are proposed in [346]. These algorithms aim to minimise the network's size while ensuring the target link availabilities due to cloud blockage. A joint strategy for GSD and routing network is proposed in [347] for satellite-terrestrial integration. CARAMUEL project [348] presents the GSD considering ground network with Quantum Key Distribution in GEO satellites. Regarding switching strategy, [349] proposes an optimal gateway selection in each moment using site diversity. In addition, to make the decision to locate these stations, we can make use of emerging technologies and techniques such as AI and ML. The application of this field for the optimized design in the GS that allows selecting the position of the gateways based on criteria beyond the service requirements is still in its infancy.

c) Proposed ML Solutions: In [350], the authors present an overview of optimization techniques applicable to solving the GW location problem. On the other hand, a survey on optimization methods based on ML focused on LEO satellite networks is performed [351]. This survey deals with GS within future autonomous transportation applications using NGSO satellites. However, it is a preliminary study using ML (LSTM) GSD techniques for SATCOM applications. For GEO satellite, DL LSTM-based GSD is detailed in [46].

3) Predistortion:

a) Motivation and Description: Power Amplifier (PA)s are among the most power-hungry components in communications systems. Therefore, PAs should work with high efficiency, consuming as little energy as possible in addition to that to be delivered. This is even more critical in power-limited devices, such as battery-operated handhelds and satellite payloads. In this regard, Radio Frequency (RF) PAs are most energy-efficient when operated at their highest output power, close to saturation. This gives rise to nonlinear effects upon the transmitted signals. The nonlinearities in the transmitter tend to degrade performance due to gain compression, clipping, phase distortion, intermodulation, adjacent channel interference, spectral re-growth, increased out-of-band emissions, etc, thus reducing the maximum throughput delivered by the payload. The basic design principle behind pre-distortion is to measure the non-linearity at the PA output side and provide a complementary non-linearity at the PA input side via analog methods in the RF domain or digital in the base band domain. SATCOM systems with digital signal processing and active beamforming capabilities could employ Digital Predistortion (DPD) techniques as part of the on-board signal processing. Applying DPD will either increase the amplifier's useful output power or increase the PAE for the same linearity requirement. A moderate increase in processor power requirement could be traded-off against either increased Power-Added Efficiency (PAE), leading to a reduction of the mass of the thermal management system, or reduced beamforming and intermodulation interference at the same PAE. These improvements have the potential to provide substantial power and mass reduction in different missions (e.g., MEO/GEO). Additionally, the use of DPD techniques will allow the use of different types of waveforms, which are currently prohibitive for SATCOMs applications, such as the OFDM based 5G-NR standard.

b) Conventional Solutions and Issues: Selecting the PAs' operation point poses significant challenges for properly balancing efficiency and linearity [352]. Limiting the output signal's Peak Envelope Power (PEP) away from the PA's saturation level (i.e., to back-off the output) improves linearity at the cost of reducing the amplifier efficiency. This approach is particularly inconvenient when dealing with high Peak-to-Average Power Ratio (PAPR) values, as those present in many current multicarrier-modulated signaling to achieve higher power spectrum efficiencies [353]. Choosing a conservative Output Back-Off (OBO) value to accommodate the PEP in the intrinsic linear part of the amplifier's characteristic implies moving the average operating point further away into the low energy efficiency regime. In other words, the higher the back-off, the lower the PAE of the PA. This justifies the need for applying additional linearizing techniques to energy-efficient but highly nonlinear amplifiers.

c) Proposed ML Solutions: ML algorithms are attractive for DPD domain due to their ability of modeling non linear behaviours. While strictly not related to SATCOM, relevant works on ML and DPD has been published in literature in recent years. Differentiating based on the dataset form used as an input for DNN, the work in [354] proposes a novel NN model based on a JANET architecture, [355] includes the phsyical features of the PA in the input of an MLP NN DPD. Paper [356] presents a DPD scheme based on a dual-time delayed neural network (TDNN) learning architecture. [357] proposes a NN to compensates the nonlinearity given by the onboard satellite payload, considered as a whole and including PA non linearity, and linear distortion caused by equipment such as filters and multiplexers.

While the application of ML techniques in the field of DPD techniques in the field of SATCOMs is still limited, we expect a widespread rise in the next future.

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

TABLE XIII: Use Cases Analysis for ML and Satellite Communication: in Magenta we highlight an on-ground ML training, in Cyan an on-board ML training

	Use Case		ML Framework					
			Supervised	Unsupervised	NN & DL	RL	DRL	FL
ML for Satellite Communication	Low Layers							
	Beamforming	Antenna Beamforming		[90], [91]	[35], [90], [92], [89]			
	Flexible Payload	Beam Hopping			[105], [97]		[43], [106]	
		Power			[42], [123]		[124]–[126]	
		Bandwidth			[145]		[43], [136]–[138]	
		Beamwidth		[33]		[33]	[157]	
	Link Adaptation		[172]		[168], [169], [171] [170]	[39]	[171]	
	Spectrum Sensing				[179]			
	Interference Management	Detection		[178]	[178], [179]			
		Classification			[177]			
	Intersatellite Synchronization		[180], [182], [183]	[184]	[181]			
	Precoding		[186]		[186]			
	Link Quality Prediction				[187]–[190]			
	Coding			[208]	[203]–[208]			
	Medium Layers							
	User Scheduling			[224], [225]				
	NOMA Access		[239], [241]	[239]	[234], [236], [239], [240] [238]		[235], [237]	
	Rate Splitting				[250], [251]		[252]	
	Constellation Routing						[257]–[259]	
	IoT Channel Access Scheduling	Fixed Access					[38], [137]	
		Random Access			[238]	[260], [265]–[267]	[235], [237] [59]	
	Upper Layers							
	Traffic/Congestion Prediction				[34], [269], [270]			
	Satellite-Terrestrial Integration		[271]	[271]	[273]	[272]		
	Edge Computing and Caching						[49], [64], [257]	[358]
	Network Security	Devices Authentication	[276]–[278]	[279]–[281]	[311]			
		Quantum Key Distribution		[284], [334]	[282], [283]			
	Outlook							
	Cooperative SATCOM				[48], [340], [341]			
	Ground Segment Dimensioning				[46], [351]			
	Predistortion				[357]			

V. Hardware Solutions

Deploying ML sets new challenges for computer processors, which will have to support large workloads as efficiently as possible in harsh environmental conditions. Satellite communication is one of those critical fields: on-ground segment applications can be less restrictive, while onboard applications can be a real challenge from the point of view of power constraints, radiation, and fault-tolerant architectures. The following HW section in this survey has multiple aims:

- The increased performance requirements for onboard processing to support higher data rates and autonomy made the previous technology obsolete. Section V-A analyzes the available non-qualified commercial offthe- shelf (COTS) ML/AI capable systems on chips for SATCOM onboard satellite applications. A comparison of modules of ML/AI techniques aimed at SATCOM on-board applications is performed from the point of view of computer power, power consumption, computer capacity per operation and form factor. In Section V-B2, we analyze the radiation challenge for on-board processing applications with COTS devices.
- Section V-A1 is dedicated to Neuromorphic Processors. An analysis for some of the use cases presented in Section IV in term of energy ration and delay ration between two latest generation chipsets based on our latest results [359].
- Section V-B illustrates the main limits and constraints of the AI/ML for SATCOM onboard operations. In Section V-B2, we analyze the radiation challenge for on-board processing applications with COTS devices.
- In addition, for each challenge, we show the most recent attempts to deploy ML SATCOM use cases proof-of-concepts and what hardware has been used to overcome the mentioned limitations.

A. Available Hardware Overview- AI-capable Chipset/Accelarators

So far, complex onboard AI/ML applications can only be performed with very expensive custom-designed application-specific integrated circuits (ASICs) [360]. ASIC devices are specifically tailored to specific functions and can also be cost-effective for high-volume production, eliminating the need for additional components and reducing power consumption.

However, ASIC development entails significant upfront costs, lengthy design and fabrication processes, and a lack of flexibility since they are tailored to specific functions. This specialization can pose risks in rapidly evolving industries, potentially leading to obsolescence and complex supply chain dependencies [361]. Despite their advantages, ASICs should be carefully considered based on application requirements, long-term viability [361].

The increased performance requirements for onboard processing to support higher data rates and autonomy made the previous technology obsolete. On-ground segment applications can be less restrictive, while onboard applications can be a real challenge from the point of view of power constraints, weight, size, radiation, and fault-tolerant architectures. New technologies, including non-qualified non-qualified commercial off-the-shelf (COTS) devices from other critical domains, are currently being explored [362]. Next, we analyze the available COTS ML/AI capable Systems on Chips for onboard satellite applications. It is worth clarifying that most of the chipsets covered in this survey require assembly on a specific board to develop applications, including at least the AI-capable chipset, a memory system, and communication interfaces.

COTS refers to products readily available from third-party vendors rather than custom-made, like ASIC. COTS products are typically mass-produced and widely available, often used in industries such as software development, electronics, and manufacturing. ML and AI algorithms can be implemented in any processing unit capable of executing the complexity and computer load of the process. Including specific ML/AI modules in the processing unit's architectures (AI-capable chipsets) reduces the CPU's computer load and increases the efficiency of the execution. COTS The architecture of AI-capable chipsets is generally formed from a central processing unit (CPU) and an on-chip accelerator, which define their capabilities and performance on AI and ML tasks. In Table XVII we have collected embedded COTS AI-enabled chipsets from the major companies[1]. The Table considers the core units as one term of comparison. The amount of CPUs and cores depends on the manufacturer and the family, ranging from one to two CPUs and two to 12 cores. Options vary from 12 cores (Jetson AGX Orin) to multi-core ARM Cortex-R5F2 on the Versal ACAP chips. The latter is suitable for embedded real-time and safety-critical systems. In contrast, the vast number of cores of the first allows the use of multi-threads in sequential parallelizable software [363], [364].

In the case of the on-chip accelerators, as their architecture differs from one developer to the other, a proper comparison considers the performance per operation or operation per second (OPs), as shown in Table XVII. OPs is a measure of a computer's performance, specifically its ability to perform arithmetic with integer values (OPs) or floating point (FLOPs). It quantifies how many calculations a processor can perform in one second (greater is better). It's often used to benchmark and compare different hardware's computational power, especially in computer architecture and ML. Note that we have marked as NR wherever some data are not reported in the literature and marked as x in case data are not detailed. As XILINX doesn't report the power consumption specifications for the Versal ACAP AI Core family, the analysis is done only for the Versal AI Core VC1902 device with the power estimation reported in

[1]Data collected from available vendor datasheets and published papers

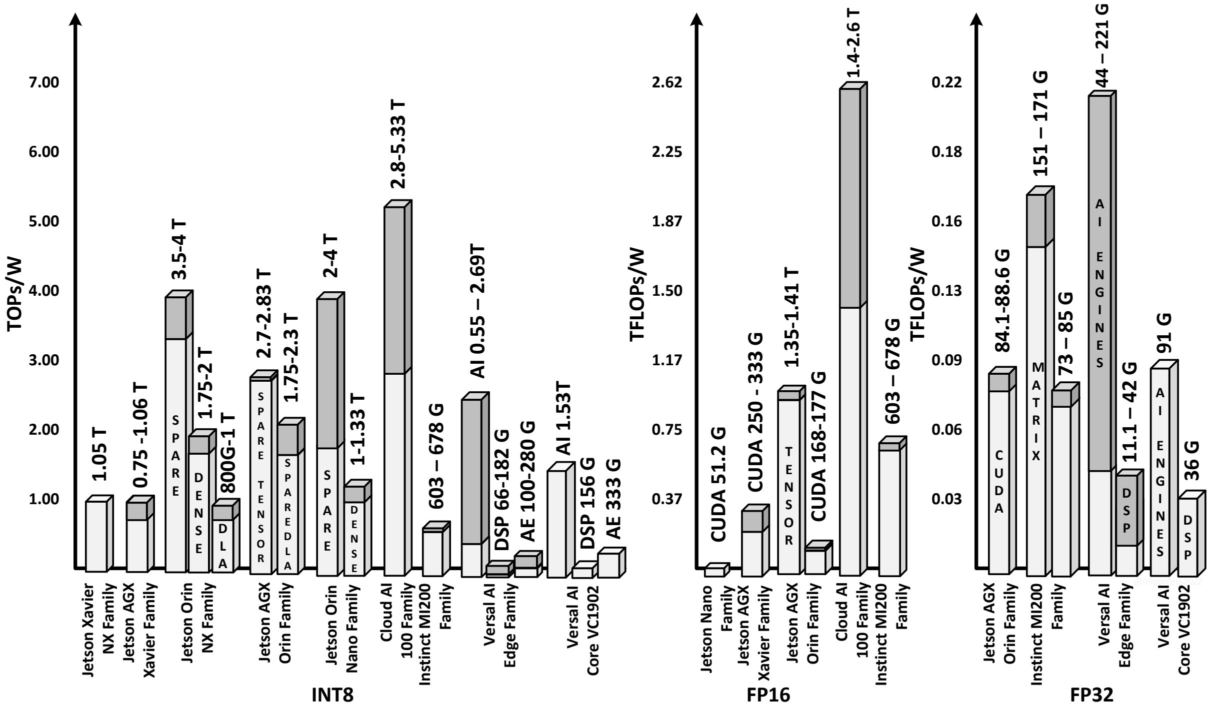


Fig. 15: AI Chipset/Accelerators off-the-shelf: Computer capacity per operation

[365].

The most supported data-types operations by the chipsets are integer bytes (INT8), half-precision floating-point (FP16), and single-precision floating-point (FP32). Instinct MI200 [366], [367] and Cloud AI 100 [368]–[370] families have the greatest operation rates in half-precision floating-point, but their form factor and power consumption make them not suitable for embedded systems applications. NVIDIA's new-generation AI processors family (Orin NX and AGX Orin [364], [371]) promises to achieve good operations per second (OPs) rate, as good as the Versal AI chip, increasing the power consumption compared to previous NVIDIA families.

It is essential to analyze the computer capacity per Watt to select the proper chipset for the application. OPs/W or FLOPs/W are a metric used to measure a computing system's energy or power efficiency. It represents the number of operations (computations or processing tasks) a system can perform in a second, normalized by the amount of power (in watts) consumed during that time. This metric is particularly important in fields where power consumption is critical, such as onboard satellite applications or energy-constrained environments like onboard space applications. Figure 15 resumes this information for the most common integer bytes operators and floating point.

This comparison proves that Versal AI Edge Family has a remarkable and wide range of performance per Watt, being a good solution for AI and ML applications for onboard Satellite Communications. Analyzing the Versal AI Core family for similar applications requires more accurate studies of chip performance.

As final terms of comparison, Table XIV also provides the dimensions of the chips along with their potential applications. Clearly, the more power the chipset consumes, the better suited for on-ground application. In addition, to minimize the risk in missions, eventual applications of AI could be limited to the payload level to perform object detection/classification locally. In this way, eventual failures of AI would only affect the quality of data for the single payload, without being a risk to the entire satellite [51]. As a reference, in [55], [60], [70] ML is deployed onboard for image classification on Myriad 2 and NVIDIA chipset. Thus, some use cases (as Beamforming, Interference Detection and Classification) utilize ML low power consuming supervised or unsupervised tasks as classification that are suited for onboard ML applications. Provided that the AI inference accelerator is supervised by a fault-tolerant engine, interference detection and antenna beamforming are good candidate for onboard applications, because the regenerative level remains at RF and antenna level [3]. Use cases that exploit ML processes that require more computational power or a more extensive training process have been indicated by us as suitable for chipsets deployed on-ground, leveraging cloud-based GPUs or more specialized training hardware. The flexible payload use case can raise concerns for its onboard applicability because it requires a regenerative payload at the low layer level due to the fact that a return channel demodulator would be required to analyze the traffic demand in real time [3].

This is further illustrated in Figure 16, which categorizes the analyzed chips by their computational performance in the most used operator data types (INT8, FP16

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

and FP32), power usage, and dimensions for various applications, and shows what hardware is best suited for on-ground or onboard applications. The Intel Myriad and NVIDIA Jetson Nano, Xavier, and Orin Nano families are classified as low-performance computing devices (<50 TOPs) suitable for on-board applications with lower power consumption [372]–[378]. The Jetson Orin NX is classified as mid-performance computing with up to 100 TOPs for on-board applications [371]. For on-board and on-ground high-performance computing, the Jetson Orin AGX, the AMD VERSAL AI Edge and AI Core are remarkable families in the range of up to 200 TOPs [364], [379], [380]. The Versal's AI families, the chip size varies from 23×23 mm^2 to 45× 45 mm^2. However, few development boards have been released. The AMD VCK190, powered by the Versal AI Core VC1902, is too big and power-demanding for onboard applications (190×241.3 mm2), while the AMD VCK5000 serves as an add-on card co-processor. The first platforms with VERSAL AI Edge Chips, dedicated to standalone applications with lower power consumption, size, and weight, are on the market from the fourth quarter of 2023 from iWave Systems and Trenz Electronics, while HiTech Global offers the VERSAL AI Core board apart from the available AMD VCK190 development board [381]–[384]. Finally, the Qualcomm AI 100 and AMD Instinct MI200 families report more significant devices with PCIe interfaces, more suitable for systems co-processors and accelerators, not for standalone and on-board applications [366]–[369].

1) Neuromorphic Processors: Mainstream microprocessors are unsuitable for deploying state-of-the-art deep neural networks that require many matrix and vector multiplication operations. This is mainly because on-chip memory, which holds the data for processing, is limited. In addition, operations involving large matrices require frequent access to off-chip memory and storage units, which consume a relatively large amount of power and take too long. The NP hardware, which can solve the resulting von Neumann bottleneck, is specifically designed to allow for tight integration of logic and memory units, and accelerator units are provided to perform frequent computational operations efficiently. Moreover, the adoption of spiking dynamics for neurons also eliminates the need for them to perform expensive multiplication operations with high-precision real numbers represented in FP32 or another reduced-precision format [41]. The most advanced hardware implementations to date are the following:

- Akida form Brainchip [385]
- TrueNorth from IBM [386]
- Loihi and Lohi2 from Intel [387]
- Zeroth from Qualcomm [388]
- SpiNNaker and SpiNNaker 2 from University of Manchester [389]
- BrainScaleS and BrainScaleS-2 from Heidelberg University [390]
- NeuroGrid and Braindrop from Stanford University [391], [392]
- DYNAP devices from SynSense [393]

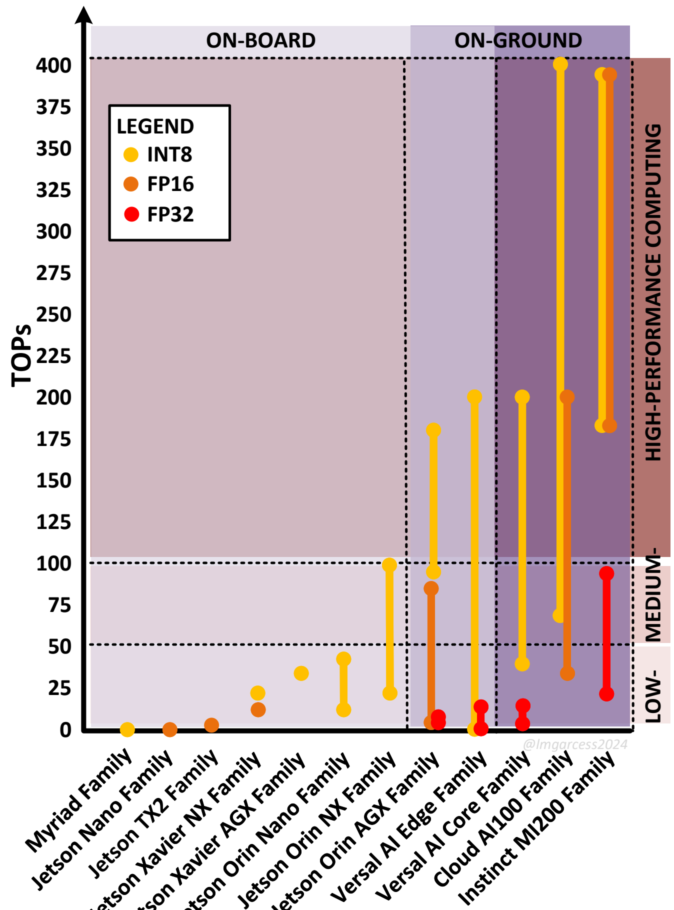


Fig. 16: AI Chipset/Accelerators off-the-shelf: Classification and use cases

- ODIN from Catholic University Louvain [394]

Table XV presents a detailed comparison of the energy consumption and convergence time (delay) for the Xilinx VCK5000 and Intel's Loihi 2 chipsets, as applied to the use case of resource optimization for flexible power and bandwidth, as discussed in Section IV [359], [395]. The energy-to-delay ratio (EDP) is a benchmark for this comparison, facilitating a direct assessment of the two technologies. In scenarios with higher EDP values, Intel's Loihi 2 shows better power and time efficiency than Xilinx's VCK5000, whereas lower EDP values indicate a more efficient performance by the VCK5000.

The comparison spans various batch sizes, indicated by 'B', reflecting the number of input samples processed. It is evident that Intel's Loihi 2 outperforms the VCK5000's CNN implementation for all tested batch sizes, although the relative advantage of Loihi 2 decreases as the batch size increases.

Specifically, for batch size 1, the table highlights the significant energy efficiency of the Loihi 2 chipset, with an energy ratio reaching as high as 13051.7. This underlines the chipset's potential for applications demanding high energy efficiency.

The impact of batch size on performance is also appar-

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

TABLE XIV: AI Chipset/Accelerators off-the-shelf: Dimension and range of application

Device	Form Factor	Range	Possible use case	Example of possible ML
Myriad Family	8~14×9.5~14 mm^2	SOM with mPCIe interface: low-performance computing requirements on-board applications	Interference Detection/Classification [55], [60]	Autoencoder, CNN
Jetson Nano	80×100 mm^2	SOM with 260-pin SO-DIMM interface: low-performance computing requirements on-board applications	Interference Detection/Classification	Autoencoder, CNN
Jetson TX2 Family	45~50×69.6~87 mm^2	SOM with 400-pin connector or 260-pin SO-DIMM interface: low-performance computing requirements on-board applications	Interference Detection/Classification	Autoencoder, CNN
Jetson Xavier NX Family	45×69.6 mm^2	SOM with 260-pin SO-DIMM interface: low-performance computing requirements on-board applications	Interference Detection/Classification	Autoencoder, CNN
Jetson AGX Xavier Family	87 × 100 mm^2	SOM with 699-pin Molex Mirror Mezz connector: low-performance computing requirements on-board applications	Interference Detection/Classification	Autoencoder, CNN
Jetson Orin NX Family	45 × 69.6 mm^2	SOM with 260-pin SO-DIMM connector interface: low- to medium-performance computing applications onboard	Beamforming, Link Adaptation	CNN, FNN, RNN
Jetson AGX Orin Family	87 × 100 mm^2	SOM with 699-pin Molex Mirror Mezz connector: for medium- to high-performance computing requirements on-board/on-ground applications	Beamforming, Flexible Payload, Link Adaptation	CNN, FNN, RNN
Jetson Orin Nano Family	45 × 69.6 mm^2	SOM with 260-pin SO-DIMM interface: low-performance computing requirements on-board applications	Interference Detection/Classification	Autoencoder, CNN
Cloud AI 100 Family	46~68.9× 110~169.5 mm^2	Addon card with PCIe interface: for medium- to high-performance computing requirements on-ground applications	Congestion Prediction, User scheduling, Flexible Payload	LSTM, SOM, Clustering, CNN
Instinct MI200 Familly	111×267 mm^2	Addon card with PCIe interface: for medium- to high-performance computing requirements on-ground applications	Congestion Prediction, User scheduling, Flexible Payload	LSTM, SOM, Clustering, CNN
Versal AI Edge Family	23~45×23~45 mm^2	SOM or Stand-alone boards: for medium- to high-performance computing requirements on-board/on-ground applications	User scheduling, Flexible Payload	LSTM, SOM, Clustering, CNN
Versal AI Core Family	35~45×35~45 mm^2	Standalone board or addon cards: for medium- to high-performance computing requirements on-board/on-ground applications	User scheduling, Flexible Payload	CNN, clustering

ent, with larger batch sizes (B=32, B=128, and B=1000) demonstrating a trend towards lower energy ratios and time ratios. This indicates a diminishing advantage for Loihi 2 with increasing batch sizes, yet it retains its superior efficiency over the VCK5000.

Overall, while the energy efficiency of flexible payload configurations may not reach the levels seen in interference detection, they consistently show an energy ratio above 100 and a time ratio below 1, underscoring the efficiency of neuromorphic computing for timely and energy-efficient solutions.

B. Hardware Analysis- Constraints and Solutions

Although ML and artificial intelligence are emerging fields for computing in-the-edge, implementing those algorithms for space applications is challenging for the scientific community due to the duration of the missions, the radiation effects on the chips, the temperature span, and the performance-to-power ratio. COTS Processors for onboard space missions require assembly into a specific board to develop the applications, including at least the AI-capable chipset, a memory system, and communication interfaces, taking into account the radiation-hardness-by-design (RHBD) or radiation-tolerance (RT) of the chip and board components, shielding, fault-detection support, correction codes, single-point thermal load, long-term support, and availability [399], [400].

The following section introduce the main limits and constraints of the AI/ML for SATCOM onboard operations. Specifically, we consider performance limitation and radiation tolerance. In addition, for each challenge, we show the most recent tentatives to deploy ML systems and what hardware has been used in the SATCOM HW testbeds who are targeting to solve the mentioned limitations and the associated use case (Table XVI).

1) Performance - Computational power and energy efficiency: Finding a device with adequate computer capacity, proper power consumption, and compliance with standards specifications for onboard and standalone applications is one of the most critical points for the implementation [3]. This is the case with the GPU for Space project (GPU4S) that uses embedded GPUs for space workloads [398]. The authors focus on four premises for achieving the results: the parallelization capabilities of the software, the comparison with the most available COTS device in the market at this moment, and the use of a benchmarking tool created as one of the milestones of the project (GPU4S Bench) reported in [401], [402]. The test was performed for the ARM Mali G-72, NVIDIA Xavier NX, NVIDIA TX2, and AMD embedded Ryzen V1605B using complex software operations for space workloads applications. The NVIDIA Xavier reported better performance for the matrix multiplication benchmark than the rest of the platforms. Regarding energy efficiency, the best choice has been either the NVIDIA Xavier NX or the TX2.

As part of the same project, in [362], Rodriguez et al. present a case study for an onboard infrared detector algorithm implementation using an embedded GPU. The algorithm is based on image matrix operations, targeting an NVIDIA Jetson Xavier's embedded GPU, using the CUDA cores for the algorithm acceleration and the Carmel CPU for offload computation. The CPU implementation, for a standard 2k $\times$ 2k pixels image, reports performances of 98 times compared with the same algorithm on the LEON2 processor and 15.5 times on the PowerPC 750, while the GPU implementation reports performances of 806 and 128 times, respectively. The authors confirm that embedded GPUs can be an option to consider in future space missions [362].

In [403], [404], the same authors continue the analysis of the existing space application domains and survey the COTS and soft-IP embedded GPU domain to assess which meets the required computational power and identify the challenges which need to be addressed for their adoption in space.

TABLE XV: Performance comparison for SatCom applications in terms of energy and time ratio for flexible power and bandwidth at various batch sizes.

Batch Size (B)	Energy (vs Loihi)	Time (vs Loihi)
1	13051.7	11.2088
32	620.69	0.43956
128	306.466	0.21978
1000	243.103	0.164835

Steenari et al. present in [399] a survey of high-performance processors and FPGAs for onboard processing and ML applications. The study includes as test device types the single and multicore processors, DPS and many-cores processors, embedded GPUs and FPGAs, while the considered data focus on the peak performance and size, qualification status, radiation support and ML tools availability. The authors conclude a significant gap in processing capabilities between RHBD/RT and COTS devices, as space processors need to catch up to commercial devices in terms of process technology and performance. However, the available COTS processors and accelerators have not been provided with RT-qualified packages. High-performance COTS processors could meet future high-performance requirements for the onboard mission. However, they could compromise mission lifetime, availability, and reliability as COTS devices usually need longer-time support.

In [405], Marques et al. analyze the feasibility of ML applications for onboard space weather detection on COTS devices. The neural network was trained to distinguish between background and radiation particles. The authors expose a set of HW devices and development tools for ML and AI. The HW tested includes FPGA devices like Zynq-7000 SoC, Zynq Ultrascale+, Kintex Ultrascale and Versal ACAP; processors like the onboard space-qualified processor (GR740/Leon4) and generic ARM Cortex A53 available in the Zynq US+ MPSoC; and SBC like Unibap iX5 and Myriad X.

Comparing the implementation results for FPGA-based platforms, Versal ACAP AI Core shows the best performance for inference on Coronal Mass Ejection (CME) Detection and Particle Detection. In contrast, Kintex Ultrascale KU040 shows the worst results [405]. In the case of microprocessors, although the results are not as good as previous platforms, the processing time of a non-optimized implementation on a single-core LEON4 is already sufficient for onboard detection with better latency than detection on the ground after downlinking. At the same time, the CNN model for the ARM Cortex A53 MPSoC needs 5.8 times more time than the FPGA implementation on the same platform. In the case of the SBC platforms, the best results are achieved using the embedded GPU (Unibap iX5 GPU) for CME Detection inference. At the same time, Myriad X gets three times better results in Particle detection Inference.

This analysis demonstrates that using dedicated HW architecture for ML and AI, such as AI Engines or embedded GPU, makes a difference in increasing the performance of implementing these types of applications.

In [365], XILINX published a solution brief for AI inference with a Versal AI Core VC1902 for vision and video processing. The exploit of the Versal AI architecture results in an adaptable accelerator that exceeds the performance, latency, and power efficiency of traditional FPGAs and GPUs for AI/ML workloads. The authors

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

TABLE XVI: HW SATCOM Ongoing Research, RRM

Project Name	Object	Ref	Use Case	HW used
Optimus-1	neuromorphic computing		intelligent control	BrainChip's Akida
Intel Neuromorphic	neuromorphic computing	[359]	beamforming, RRM, spectrum coexistence	Loihi
TechEdSat-13	neuromorphic computing		testing	HW Loihi
ESA Spaice	on-board ML processing	[396], [397]	beamforming, RRM, flexible payload	iW-RainboW-G57D & VCK190
GPU4S Bench	COTS chipset on on-board AI applications	[398]	space workloads applications	RM Mali G-72, NVIDIA Xavier NX and NVIDIA TX2, AMD Ryzen V1605B
	GPU for on-board operation	[362]	GPU for on-board operation	NVIDIA Jetson Xavier

ensure the delivery of 2.7 times the performance per watt over competing with Intel Agilex FPGA, using 87 watts of power, estimated using the XILINX Power Estimator (XPE) tool. Even when this implementation proves this device's capability to perform highly complex operations in ML and AI applications, the power consumption is too high for onboard satellite applications.

ESA SPAICE project aims to enhance SATCOM using AI-based signal processing techniques using COTS devices for space applications. It involves developing methods for signal identification, spectrum monitoring, sharing, and demodulation using an off-the-shelf AI chipset. A laboratory test bed is being developed to validate these techniques in both on-ground and on-board scenarios [396], [397]. The AI platform for the payload system is composed of two main COTS boards: iWave's Versal AI Edge SOM Development platform[2] and HiTech Global's Xilinx Zynq UltraScale+ RFSoC FMC+ (Vita57.4) Platform. The iWave's Versal AI Edge SOM Development platform (as AI platform) offers high-performance AI acceleration capabilities and is suitable for edge computing applications [381]. On the other hand, HiTech Global's Xilinx Zynq UltraScale+ RFSoC FMC+ Platform (as RF front-end) is based on the Xilinx Zynq UltraScale+ RFSoC FPGA and utilizes the FMC+ (Vita57.4) standard [406]. By combining these two platforms, the payload system can leverage the AI processing capabilities of the Versal AI Edge SOM while utilizing the RF and high-speed data processing capabilities of the Zynq UltraScale+ RFSoC FPGA. This enables the system to perform advanced AI tasks and handle RF-related functions simultaneously.

INTEL has funded the Intel Neuromorphic Research Community, which includes academic, government, and corporate groups worldwide engaged in advancing the science and application of ML-based neuromorphic computing using Intel's Loihi neuromorphic processor. Possible use cases of Neuromorphic computing include beamforming, radio resource management, spectrum coexistence. and interference mitigation [41]. NP research in [359] utilizes a Xilinx Versal VCK5000 compared with a LOIHI 2 in terms of energy consumption and convergence time.

Alpha Data announced in October 2023 the onboard Off-the-Shelf Development Platform for Space 2.0 ADK-VA600 based on the space-qualified AMD Versal AI Core XQRVC1902 AI-capable chipset. This technology signifies a substantial enhancement in performance, specifically catering to compute-intensive applications such as Signal Processing and Machine Learning in space. It considers critical factors like a limited radiation environment and mission duration, particularly relevant for Low Earth Orbit (LEO) applications [407], [408].

2) Radiation tolerance: Despite being made of materials like aluminum, satellites are still vulnerable to space radiation due to their orbits and the types of particles they encounter. Orbits can expose satellites to different levels and types of radiation, including high-energy particles from the sun and cosmic rays [409], [410]. It follows that AI/ML developed for commercial use in SATCOM must be designed to tolerate radiation. Although none of the COTS AI capable devices is considered radiation-hardened by design, new studies are emerging to use the COTS chipset in onboard AI applications [411]. The current specifics of the radiation levels to which the satellite components can be exposed have been designed by NASA and depend on the orbit and inclination of the satellite. For space vehicles or satellites in low inclination LEO in both the northern and southern hemispheres, typical dose rates due to trapped Van Allen electrons and protons are 100-1000 rad(Si)/year. For space vehicles or satellites in higher inclination LEO in both the northern and southern hemispheres, typical dose rates due to the increase in the number of trapped electrons are 1000-10,000 rad(Si)/year [410]–[413].

The strategies for mitigating the effects of radiation include metallic shielding, a classic method to reduce exposure to space radiation. It absorbs and deflects radiation, providing a protective barrier for sensitive equipment [409], [414]. The use of qualification of COTS items is another interesting approach. This involves testing and ensuring that commercially available components are suitable for space environments. Drawing from successful experiences in in-orbit testing can provide valuable insights into the performance of these components in real-world conditions [411], [415].

If the application focuses on onboard satellite applications, the constraints for the board construction become more severe. Processing input data and implementing ML models require a large amount of computation, often performed by custom integrated circuits. Radiation exposure can cause errors in these circuits, resulting in hardware and software failures [51]. AMD announced the release of the first Space-Grade Versal Adaptative SoCs enabling onboard AI processing in space [360], [405], [416]. The actual information about this device pointed out that the XQR Versal AI Core XQRVC1902, to be available

[2]In the prototype stage of the project a VCK190 board was used, featuring a Versal AI Core VC1902

in early 2023, will be based on the XILINX Versal AI Core VC1902, detailed in Section V-A, including Class B qualification, radiation-tolerance and a 45×45 mm^2 packing [416]. There is yet no information on the possible power consumption, the principal inconvenience of its predecessor, and the computer capacity of the chip.

Current studies are also ongoing to develop neuromorphic computing solutions resistant to space-related impairments. The work in [40] considers strategies to overcome events of power interruptions that occur in metal oxide materials.

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

TABLE XVII: AI Chipset/Accelerators off-the-shelf: Core Units

Device	Provider	Core Units: CPU	Core Units: On-chip accelerator	Computer Capacity in operations: I8 (Ops)	Computer Capacity in operations: FP16 (FLOPs)	Computer Capacity in operations: FP32 (FLOPs)	Power (W)
Myriad Family	Intel	2x Leon 4 RISC	Image/Video PA	NR	NR	NR	1~2
			SHAVE				
Jetson Nano	NVIDIA	4x ARM Cortex-A57MP	128-CUDA Maxwell	NR	512G	NR	5-10
Jetson TX2 Family	NVIDIA	2x ARM64b Denver	256-CUDA Pascall	NR	x	NR	7.5-20
		4x ARM Cortex-A57MP					
Jetson Xavier NX Family	NVIDIA	6x ARM64b Carmel	384-CUDA Volta	21T	x	NR	10-20
			2x NVDLA				
			2x PVA				
			48 Tensor				
Jetson AGX Xavier Family	NVIDIA	8x Carmel ARM64b	512-CUDA Volta	30-32T	10T	NR	10-40
			2x NVDLA				
			2x PVA				
			64 Tensor				
Jetson Orin NX Family	NVIDIA	6x/8x ARM64b Cortex-A78AE	1024-CUDA Ampere	70-100T Sparse	x	x	10-25
			1x/2x NVDLAv2	1-1.33T Dense			
			1x PVAv2	20T Sparse			
			32 Tensor				
Jetson AGX Orin Family	NVIDIA	8x/12x ARM64b Cortex-A78AE	1782/2048-CUDA Ampere	108-170T Sparse	58-85T	3.3-5.3T	15-60
			2x NVDLAv2	92-105T Sparse	67-106T		
			1x PVAv2				
			56/64 Tensor				
Jetson Orin Nano Family	NVIDIA	6x ARM64b Cortex-A78AE	512/1024-CUDA Ampere	2-4T Sparse	x	x	5-15
			16/32 Tensor	1-1.33T Dense			
Cloud AI 100 Family	Qualcomm	Snapdragon 865 MP	Cloud AI 100	70–400T	35-200T	x	15-75
		Kryo 585 CPU					
Instinct MI200 Familly	AMD	CDNA2	6656/14080-Stream Proc.	181-383T	181-383T	45.3-95.7T (Matrix)	300-560
			104/220 Core Units			22.6 - 45.9T	
Versal AI Edge Family	AMD XILINX	2x ARM64 Cortex-A72	8-304 AI Engines/ML	5-202T	NR	0.4-16.6T	6-75
		2x ARM Cortex-R5F2	90-1312 DSP Eng	0.6-9.1T		0.1-2.1T	
			43k-1139k System Logic Cells	1-17T			
Versal AI Core Family	AMD XILINX	2x ARM64 Cortex-A72	128-400 AI Engines	133T	NR	8T	~87
		2x ARM Cortex-R5F2	928-1968 DSP Eng	13.6T		3.2T	
			504k-1968k System Logic Cells	29T			

VI. Challenges and Open Discussion

A. Dataset for training

1) Training datasets Availability: The availability of real-world datasets is one of the most crucial preconditions for evaluating any proposed ML based method. So far, the cost and access difficulty of highly representative datasets has hindered the development in SATCOM of ML techniques. In fact, while some learning approaches can be trained with small simulated datasets, advanced techniques such as DL and DRL requires a large dataset to converge and reach the desired performance. It is time consuming and costly to generate a large dataset for SATCOM using simulators. In addition, even assuming large datasets can be produced via simulations, their accuracy remains a key open discussion point. This review paper has shown that the development of the ML research does not go hand in hand with the development and availability of training datasets. Most open source datasets are datasets to train ML models on satellite imagery [417]–[419] and it is pretty rare to find open high-resolution datasets for the other use cases presented in Section IV. The result is that computing the accuracy and scalability of the proposed ML models in the real world is a challenge.

2) Data Dimensionality Reduction: Using large data dimensions during learning and testing increases computational complexity and slows the decision-making process. A promising solution to this problem is mapping the data from high dimension space to a lower one while preserving the most relevant and important features. Specifically, data dimensionality reduction is the process of scaling down a set of data with high dimensions to data with lower dimensions, ensuring that it concisely conveys similar information without affecting the original information. Data dimensionality reduction removes irrelevant, noisy, and redundant data to obtain acceptable accuracy. In SATCOM systems, high-dimensional datasets are naturally aggregated from heterogeneous data sources and massive data streams, causing many processing challenges. Thus, it is essential to find optimal techniques or solutions for dimensionality reduction while catering to the effect of reducing high-dimensional data without compromising the data value. Selecting an appropriate data dimension reduction technique will expedite the processing time and reduce the efforts required to extract insightful information.

The data representation space size can be reduced via feature extraction or selection techniques. The feature extraction transforms the initial data attributes into a new one formed by the linear or non-linear combination of the initial attributes. Contrarily, the feature selection method identifies the most relevant attributes according to some given criteria. In this context, different dimensionality reduction techniques are available in the literature to eliminate irrelevant and redundant features, and the work in [420] has reviewed the existing dimensionality reduction techniques and their suitability for different types of data and application areas highlighting the issues that may affect the accuracy and relevance of the obtained results. Furthermore, an unsupervised deep-learning framework named local deep-feature alignment (LDFA) for dimension reduction has been developed in [421] to extract the essential features. In addition, two-dimensionality reduction techniques, linear discriminant analysis (LDA) and principal component analysis (PCA) are investigated in [422] on some popular Machine Learning algorithms.

In this direction, the work in [423] has proposed using the Random Forest imputation method to extract useful information and reduce the search space to facilitate data exploration. Moreover, a combination of convolutional deep belief network (CDBN) with autoencoding feature algorithm is applied for data dimensionality reduction and layer-wise learning [424]. Specifically, CDBN is a hierarchical generative model that employs probabilistic max-pooling to extract high-level features by replacing the restricted Boltzmann machine (RBM) in the deep belief networks used for the individual layers by convolutional RBMs. Thus, this technique has been shown to be an efficient algorithm for dimensionality reduction, collaborative filtering, and faster feature learning [425]. Likewise, Auto-Encoder and PCA approaches are used for dimensionality reduction in [426] to design intrusion detection systems with ML. Reference [427] has considered multivariate statistical methods like independent component analysis (ICA) and minimum noise fraction (MNF) as dimensionality reduction techniques for processing satellite data.

B. Future AI Frontiers/Visions for Satellite Communication

1) Federated Learning: SATCOM's deployment of systems globally has led to an increasing demand for ML solutions operating in distributed systems. In this regard, the federated ML approach has emerged as a promising solution to deploy ML models in global IoT systems such as SatCom [428].

The federated ML approach refers to training ML models on multiple devices, each of which performs a part of the training process on its local data. Instead of sending data to a centralized server for training, the data is maintained on local devices, and only model updates are sent to the server. This collaborative learning approach can provide a scalable and decentralized solution for training models on large data sets without requiring data transfer between devices.

However, the federated ML approach also presents some technical challenges. First, local devices and the central server must communicate reliably to ensure data integrity and model updates. In addition, federated ML models need to be able to handle heterogeneous data and devices with different processing capabilities.

Another major challenge is ensuring data privacy and security. Because data is held on local devices, robust security and privacy measures must be implemented to protect user and organizational data.

2) ML and Blockchain: Security and resilience are features claimed by the new constellations and satellite systems, especially for Earth observation applications or Government communications such as those provided by the GOVSATCOM project. The typical long distances in SATCOM lead to significant communication delays among the network nodes, compromising the data's integrity and reliability. Establishing prioritized, secure, and efficient command and data communication is essential for space and ground systems. Using Blockchain (BC) assures a secure automated network infrastructure for many applications in SATCOM, including autonomous satellite constellation control through satellite-to-satellite communication, prioritized and stable data and command communication between space and ground stations, among others. Similarly, BC networks can benefit from SATCOM thanks to their broad geographic reach and broadcast capabilities. The BC-based network nodes participate by receiving and sending data across the distributed network architecture. The data maintain a unique structure transferred by transactions [429]. These data can be anything, such as personally identifiable data, satellite command, or key/value paired asset data stored on blocks and linked together in a chain. Any alteration in a transaction detects an introduction or threat in the communication, directly invalidating the transmission. The BC application to benefit SATCOM has been proposed for different use cases such as interference detection in [430], spectrum management in [431], satellite manufacturing supply chain in [432], and Space Situational Awareness in [433]. Different contributions of BC in the space industry are identified in [434]. Some of them are (1) identity authentication and exchanged data integrity for LEO satellites which include its dynamic topology and regular link switching, and (2) reducing complexity across a range of business, operational, and security applications using smart contracts by BC networks. In [435], from the point of view of communication, a solution to reduce end-to-end latencies in SATCOM is proposed based on a BC-based reputation framework and routing protocol. ML in blockchain applications applied to SATCOM is currently a crucial challenge where only a few preliminary works are presented in the literature. Notably, Space-Air-Ground Integrated Networks (SAGIN) project in [436] presented a federated RL approach to trusted traffic offloading using BC.

3) Tiny Machine Learning for Satellite: TinyML deploys ML algorithms onto low-cost, low-power and limited resource devices, storing NN models directly within memory and directly running inference on onboard sensors' output. TinyML aims to create algorithms and software capable of performing efficiently on intelligent or limited resources edge devices. This approach avoids communicating with the cloud to transmit data for external processing.

TinyML aims to improve the efficiency of DL AI systems by requiring far less computation power, a less costly hardware platform and improving energy efficiency. [437] shows that TinyML is capable of using a fraction of the compute resources needed for traditional ML systems. Finally, while the heterogeneity and limited resources of MCU devices present new challenges for on-device training, model updating, and deployment, recent research and the development of MLframeworks such as TensorFlow Lite for Microcontrollers have increased the accessibility of TinyML. Due to its nature, TinyML is one of the fastest growing areas of DL and might become a disruptive application in SATCOM.

4) Quantum Computing and AI: We have shown (Section IV-C5) the importance of quantum communication for SATCOM in its role of ultra-secure communication. Beyond this, quantum computing holds great potential for AI developers looking to create more advanced AI systems that can solve problems faster and more efficiently. Specifically, quantum computing may make AI training process faster as it allows utilizing larger datasets to train AI models to be more accurate and better at decision-making. Although quantum computing is still in its early development stages, there are several imminent benefits AI can gain from quantum computers, including but not limited to:

- Increased computational power: Quantum computers have the capability of solving some complex optimization problems exponentially faster than classical computers. This could open up new possibilities for AI development, such as enabling more complex ML algorithms to be trained in less time. For instance, quantum computers can help AI developers to optimize complex functions more efficiently by leveraging quantum annealing and other optimization techniques that are not available in classical computing [438], [439].
- Improved algorithm development: Quantum computing can suppport AI developers improve existing algorithms or develop new ones that can take advantage of the unique capabilities of quantum computing. For example, quantum ML algorithms can leverage quantum entanglement and superposition to achieve better accuracy in some specific instances and faster training [440].
- Enhanced data analysis: Quantum computing can help analyze larger datasets more efficiently and identify patterns that are difficult to detect using classical computing. This can lead to improved data-driven decision-making and insights [441].
- Quantum communications provide a means of safeguarding the confidential data used by AI systems from hacking and other forms of cybercrime.

Furthermore, a major challenge in the operation of the CubeSats and small satellites within NTNs in lower altitudes is the rather low information processing capabilities of the onboard processors. Consequently, developing and utilizing AI models in these entities can be beyond the capability of a single satellite processor. Due to the large dimension of quantum computer, the use of quantum computing is specific to cloud-based quantum computing

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

where the CubeSats or other satellites with low on-board computational power can offload complex computational tasks to the on-ground quantum computers. Some of the notable cloud quantum computing frameworks with access to physical quantum computers available today include Amazon braket, IBM Q, and D-Wave's Leap [442]–[444]. Thus, a space quantum network can be structured and interconnected via FSO links, which will benefit from the high computational capacity of quantum servers with certainly enhanced security performance to efficiently use AI and ML techniques [445].

5) AI and Optimization Methods: This paper has shown that ML and AI have tremendous potential in future SATCOM networks. Thus, while it is clear that the next generation of satellites will rely on AI, it is unclear how AI should be integrated into the architecture of satellite networks. Most of the data-driven approaches surveyed (see table XIII) are based on NN and DRL techniques that require a large amount of data and are complex to process. Therefore, it is convenient to investigate how to mitigate the computational complexity, latency, and power consumption.

External knowledge can be incorporated as an initialization procedure [446] or leveraged in the learning approach, as in deep unfolding [447]. In the former, the training set for the DNN can be generated offline, reducing the burden on the satellite to deal with the high complexity of the model. The model can thus be optimized online with few empirical data. The intuition behind this approach is that, although generally not perfectly accurate, the initial DNN contains some critical features of the satellite network, and less data are needed to reach the desired accuracy compared to the case where no training is performed. In the latter, NNs impacts the complexity and computational requirement of the ML model on the satellite. For instance, deep unfolding aims to map an iterative algorithm into a learnable NN and to determine the number of nodes by the number of iterations of the algorithm [209]. Deep unfolding offers the possibility of initializing a NN and refining it using empirical data. The first attempts to utilize Deep Unfolding for SATCOM applications have been mentioned in the Rate Splitting Use Case with the mentioned works [250], [251]. To reduce the complexity of power allocation and timeslot-terminal assignment in satellite NOMA systems, we have shown in this paper that the work in [236] makes use of a hybrid approach to low the complexity of the problem without, however, proposing an end to end NN that may not be feasible.

While an extensive description of hybrid ML models is beyond the scope of this paper, we believe that incorporating expert knowledge in ML models will receive increasing attention in the next future to overcome the conventional NN complexity and the relative challenges presented in Section VI-A.

C. Security and Privacy

We have shown in this survey how big data is the core of many SATCOM research activities. In fact, Image Processing and Remote Sensing AI developments rely on the data collected by satellites and drones and use it to train models for different outputs and use-cases. For this reason, AI/ML tools used to handle and analyze various sources of data are closely related to several ethical issues, not only the well-known privacy issue. Together with it, explainability, bias and ethical issues are becoming increasingly important as a result of data collection, the approaches used for analysis, the manner and purpose for which the results of such analyses are used [448].

Security aspects are crucial in the satellite communications industry and the use of ML introduces new challenges. One of the biggest risks is the potential manipulation of training data and exploitation of vulnerabilities in the trained ML model, which could adversely affect the quality of transmitted data and the integrity of the SatCom system. In addition, the use of real-time ML systems also introduces the possibility of real-time attacks, such as malicious data injection into the ML model.

An additional major challenge is the need to ensure the privacy and security of the data used to train the ML models. In particular, the collected and processed data may be sensitive to privacy, such as location or enterprise customer data. Appropriate measures must be taken to protect these data and ensure that they are only used for legitimate purposes.

The security of the hardware and software used to implement the ML models is also an important consideration. SatCom systems must be designed and built with security in mind, including protection against physical and logical attacks. The exploitation of vulnerabilities in the hardware or software used to implement the ML could have serious consequences for the integrity of the SatCom system.

D. Cost Optimization

Cost optimization is a critical factor in the satellite communications industry, and the deployment of artificial intelligence technologies is no exception. When considering the deployment of ML systems, the costs of the necessary components and the resources required to train and maintain the ML models must be considered. In addition, the cost of putting a satellite in orbit must also be considered and the cost-benefit optimization of ML systems must be sought.

The cost of deploying a Gbps in orbit can be extremely high [449]. The weight of the satellite components and associated power consumption can also be costly in terms of satellite payload capacity and battery life. Therefore, more efficient and cost-effective design solutions, such as using low-power data processing technologies and optimizing ML algorithms to minimize the required resources, should be explored.

Cost optimization must also consider the scalability of ML systems. As more and more satellites are deployed, scalable and cost-effective solutions must be found to train and maintain ML models on all satellites. This may include using distributed computing technologies and

This article has been accepted for publication in IEEE Communications Surveys & Tutorials. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/COMST.2025.3534617

implementing automation solutions to reduce maintenance and training costs.

VII. Conclusions

This article has captured the latest technical advances in scientific, industrial and standardisation analyses in the domain of satellite communications and AI/ML. In particular, the most important applications and use cases under the current focus of AI for SATCOM research have been highlighted. The communication testbeds which have been developed in order to practically demonstrate some of the advanced SATCOM concepts are shown.

Finally, some important future challenges and their respective open research topics have been described.

Acronyms

3GPP	3rd Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
6G	Sixth Generation
A2G	Air to Ground
ABF	adaptive beamforming
ACM	Adaptive Coding and Modulation
AI	Artificial Intelligence
AoI	Age of Information
ASIC	application-specific integrated circuit
BC	Blockchain
BH	Beam Hopping
C-RAN	Cloud Radio Access Networks
CCNN	Clustering and Classification Neural Network
CDMA	Code Division Multiple Access
CN	Core Network
CNN	convolutional neural network
COTS	non-qualified commercial off-the-shelf
CR	Cognitive Radio
CSI	channel state information
DDPG	Deep Deterministic Policy Gradient
DL	deep learning
DNN	deep neural network
DPD	Digital Predistortion
DQL	Deep Q-learning
DRL	deep reinforcement learning
DRT	Dehop-rehop Transponder
DSS	Dynamic Spectrum Sharing
DU	Deep Unfolding
EIRP	Effective Isotropic Radiated Power
EO	Earth Observation
ESA	European Space Agency
ESN	Echo state network
FDMA	Frequency Division Multiple Access
FEC	Forward Error Correction
FH-FDMA	frequency hopping-frequency division multiple access
FL	Federated Learning
GA	Genetic Algorithms
GEO	Geo-Stationary Orbit
GNSS	Global Navigation Satellite System
GSO	Geosynchronous Orbit
GW	gateway
HAP	High Altitude Platform
IoT	Internet of Things
ISS	International space station
KPI	Key Performance Indicator
LAP	Low Altitude Platform
LDA	linear discriminant analysis
LEO	Low Earth Orbit
LMS	Least Mean Squares
LP	Linear Precoding
LSTM	Long Short-term Memory
M2M	Machine-to-machine
MADRL	multi-agent deep reinforcement learning
MDP	Markov Decision Process
MEC	Mobile Edge Computing
MEO	Medium Earth Orbit
MILP	Mixed-Integer Linear Programming
MIMO	multiple-input multiple-output
ML	machine learning
MLCNN	Multi-Label Classification Neural Network
MMSE	Minimum Mean-Square Error
NAS	Neural Architecture Search
NFV	Network Function Virtualization
NGSO	Non Geo-Stationary
NN	neural network
NOMA	Non-orthogonal Multiple Access
NP	Neuromorphic processor
NR	New Radio
NTN	Non-terrestrial network
OAI	OpenAirInterface
OBO	Output Back-Off
OFDM	Orthogonal Frequency-division Multiplexing
OFDMA	Orthogonal Frequency-Division Multiple Access
OMA	Orthogonal Multiple Access
OPEX	Operational Expenditure
PA	Power Amplifier
PAE	Power-Added Efficiency
PAPR	Peak-to-Average Power Ratio
PCA	principal component analysis
PEP	Peak Envelope Power
PGD	Projection Gradient Descent
PKC	Public-key Cryptosystem
PLS	physical-layer security
PoP	Point of Presence
PSO	Particle Swarm Optimization
QKD	quantum key distribution
QoS	Quality of Service
RAN	Radio Access Network

RF	Radio Frequency
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RRM	Radio Resource Management
RTT	Round Trip time
RZF	Regularized Zero Forcing
SAGIN	Space-Air-Ground Integrated Network
SATCOM	satellite communication
SCS	Satellite Communication System
SDMA	Spaced Division Multiple Access
SDN	Software Defined Network
SIC	Successive Interference Cancellation
SKC	Secret-key Cryptosystem
SLL	side lobe level
SNR	Signal-to-Noise Ratio
ST	Satellite Terminal
SVM	Support Vector Machine
TDMA	Time Division Multiple Access
TEG	Time-expanded Graph
TN	Transport Network
UAV	Unmanned Aerial Vehicle
UE	User Equipment

References

[1] G. Geraci, D. Lopez-Perez, M. Benzaghta, and S. Chatzinotas, "Integrating terrestrial and non-terrestrial networks: 3d opportunities and challenges," IEEE Communications Magazine, 2022.

[2] M. Á. Vázquez, P. Henarejos, A. I. Pérez-Neira, E. Grechi, A. Voight, J. C. Gil, I. Pappalardo, F. Di Credico, and R. M. Lancellotti, "On the Use of AI For Satellite Communications," arXiv preprint arXiv:2007.10110, 2020.

[3] F. Ortiz, V. Monzon Baeza, L. M. Garces-Socarras, J. A. Vásquez-Peralvo, J. L. Gonzalez, G. Fontanesi, E. Lagunas, J. Querol, and S. Chatzinotas, "Onboard processing in satellite communications using ai accelerators," Aerospace, vol. 10, no. 2, p. 101, 2023.

[4] C. Jiang, H. Zhang, Y. Ren, Z. Han, K.-C. Chen, and L. Hanzo, "Machine Learning Paradigms for Next-generation Wireless Networks," IEEE Wireless Commun., vol. 24, no. 2, pp. 98–105, 2016.

[5] D. Bega, M. Gramaglia, A. Banchs, V. Sciancalepore, and X. Costa-Pérez, "A Machine Learning Approach to 5G Infrastructure Market Optimization," IEEE Trans. Mob. Comput., vol. 19, no. 3, pp. 498–512, 2019.

[6] M. M. Azari, S. Solanki, S. Chatzinotas, O. Kodheli, H. Sallouha, A. Colpaert, J. F. M. Montoya, S. Pollin, A. Haqiqatnejad, A. Mostaani et al., "Evolution of Non-terrestrial Networks from 5G to 6G: A survey," IEEE Commun. Surveys Tuts., 2022.

[7] O. Kodheli, E. Lagunas, N. Maturo, S. K. Sharma, B. Shankar, J. F. M. Montoya, J. C. M. Duncan, D. Spano, S. Chatzinotas, S. Kisseleff et al., "Satellite Communications in the New Space Era: A Survey and Future Challenges," IEEE Commun. Surveys Tuts., vol. 23, no. 1, pp. 70–109, 2020.

[8] T. Hoeser and C. Kuenzer, "Object detection and image segmentation with deep learning on earth observation data: A review-part i: Evolution and recent trends," Remote Sensing, vol. 12, no. 10, p. 1667, 2020.

[9] S. Walsh, D. Murphy, M. Doyle, J. Reilly, J. Thompson, R. Dunwoody, J. Erkal, G. Finneran, G. Fontanesi, J. Mangan et al., "Development of the eirsat-1 cubesat through functional verification of the engineering qualification model," Aerospace, vol. 8, no. 9, p. 254, 2021.

[10] N. Saeed, A. Elzanaty, H. Almorad, H. Dahrouj, T. Y. Al-Naffouri, and M.-S. Alouini, "Cubesat communications: Recent advances and future challenges," IEEE Communications Surveys & Tutorials, vol. 22, no. 3, pp. 1839–1862, 2020.

[11] P. K. Chowdhury, M. Atiquzzaman, and W. Ivancic, "Handover Schemes in Satellite Networks: State-of-the-art and Future Research Directions," IEEE Communications Surveys & Tutorials, vol. 8, no. 4, pp. 2–14, 2006.

[12] H. Al-Hraishawi, H. Chougrani, S. Kisseleff, E. Lagunas, and S. Chatzinotas, "A Survey on Non-geostationary Satellite Systems: The Communication Perspective," IEEE Commun. Surveys Tuts., 2022.

[13] L. M. Marrero, J. C. Merlano-Duncan, J. Querol, S. Kumar, J. Krivochiza, S. K. Sharma, S. Chatzinotas, A. Camps, and B. Ottersten, "Architectures and Synchronization Techniques for Distributed Satellite Systems: A Survey," IEEE Access, vol. 10, pp. 45 375–45 409, 2022.

[14] P.-D. Arapoglou, K. Liolis, M. Bertinelli, A. Panagopoulos, P. Cottis, and R. De Gaudenzi, "Mimo over Satellite: A Review," IEEE communications surveys & tutorials, vol. 13, no. 1, pp. 27–51, 2010.

[15] M. De Sanctis, E. Cianca, G. Araniti, I. Bisio, and R. Prasad, "Satellite Communications Supporting Internet of Remote Things," IEEE Internet Things J., vol. 3, no. 1, pp. 113–123, 2015.

[16] M. Centenaro, C. E. Costa, F. Granelli, C. Sacchi, and L. Vangelista, "A survey on technologies, standards and open challenges in satellite IoT," IEEE Commun. Surveys Tuts., vol. 23, no. 3, pp. 1693–1720, 2021.

[17] B. A. Homssi, K. Dakic, K. Wang, T. Alpcan, B. Allen, S. Kandeepan, A. Al-Hourani, and W. Saad, "Artificial Intelligence Techniques for Next-Generation Mega Satellite Networks," arXiv preprint arXiv:2207.00414, 2022.

[18] V. Kothari, E. Liberis, and N. D. Lane, "The final frontier: Deep learning in space," in Proceedings of the 21st international workshop on mobile computing systems and applications, 2020, pp. 45–49.

[19] M. Lofqvist and J. Cano, "Accelerating deep learning applications in space," arXiv preprint arXiv:2007.11089, 2020.

[20] A. Russo and G. Lax, "Using Artificial Intelligence for Space Challenges: A Survey," Applied Sciences, vol. 12, no. 10, p. 5106, 2022.

[21] K. Lu, H. Liu, L. Zeng, J. Wang, Z. Zhang, and J. An, "Applications and prospects of artificial intelligence in covert satellite communication: a review," Science China Information Sciences, vol. 66, no. 2, p. 121301, 2023.

[22] F. Fourati and M.-S. Alouini, "Artificial Intelligence for Satellite Communication: A Review," Intelligent and Converged Networks, vol. 2, no. 3, pp. 213–243, 2021.

[23] J. Wang, C. Jiang, H. Zhang, Y. Ren, K.-C. Chen, and L. Hanzo, "Thirty years of machine learning: The road to pareto-optimal wireless networks," IEEE Communications Surveys & Tutorials, vol. 22, no. 3, pp. 1472–1514, 2020.

[24] Y. Sun, M. Peng, Y. Zhou, Y. Huang, and S. Mao, "Application of machine learning in wireless networks: Key techniques and open issues," IEEE Communications Surveys & Tutorials, vol. 21, no. 4, pp. 3072–3108, 2019.

[25] X. Zhu and C. Jiang, "Integrated satellite-terrestrial networks toward 6g: Architectures, applications, and challenges," vol. 9, no. 1, pp. 437–461, conference Name: IEEE Internet of Things Journal.

[26] R. De Gaudenzi, M. Luise, and L. Sanguinetti, "The open challenge of integrating satellites into (beyond-) 5g cellular networks," IEEE Network, vol. 36, no. 2, pp. 168–174, 2022.

[27] F. G. Ortiz-Gomez, L. Lei, E. Lagunas, R. Martinez, D. Tarchi, J. Querol, M. A. Salas-Natera, and S. Chatzinotas, "Machine Learning for Radio Resource Management in Multibeam GEO Satellite Systems," Electronics, vol. 11, no. 7, p. 992, 2022.

[28] T. M. Mitchell and T. M. Mitchell, Machine Learning. McGraw-hill New York, 1997, vol. 1, no. 9.

[29] Y. Zhao, Y. Li, X. Zhang, G. Geng, W. Zhang, and Y. Sun, "A survey of networking applications applying the software defined networking concept based on machine learning," IEEE Access, vol. 7, pp. 95 397–95 417, 2019.

[30] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," nature, vol. 521, no. 7553, pp. 436–444, 2015.

[31] W. G. Hatcher and W. Yu, "A survey of deep learning: Platforms, applications and emerging research trends," IEEE Access, vol. 6, pp. 24 411–24 432, 2018.

[32] R. Collobert and S. Bengio, "Links between perceptrons, mlps and svms," in Proceedings of the twenty-first international conference on Machine learning, 2004, p. 23.

[33] F. G. Ortiz-Gomez, D. Tarchi, R. Martínez, A. Vanelli-Coralli, M. A. Salas-Natera, and S. Landeros-Ayala, "Convolutional neural networks for flexible payload management in vhts systems," IEEE Systems Journal, vol. 15, no. 3, pp. 4675–4686, 2021.

[34] P. Henarejos, M. A. Vazquez, and L. Blanco, "Traffic congestion prediction in satellite broadband communications," in Proceedings of the 39th International Communications Satellite Systems Conference (ICSSC), 2022.

[35] I. Mallioras, Z. D. Zaharis, P. I. Lazaridis, and S. Pantelopoulos, "A Novel Realistic Approach of Adaptive Beamforming Based on Deep Neural Networks," IEEE Trans. Antennas Propag, 2022.

[36] M. Á. Vázquez, P. Henarejos, I. Pappalardo, E. Grechi, J. Fort, J. C. Gil, and R. M. Lancellotti, "Machine Learning for Satellite Communications Operations," IEEE Commun. Mag., vol. 59, no. 2, pp. 22–27, 2021.

[37] H. Al-Hraishawi, M. Minardi, H. Chougrani, O. Kodheli, J. F. M. Montoya, and S. Chatzinotas, "Multi-layer space information networks: Access design and softwarization," IEEE Access, 2021.

[38] J. Liu, B. Zhao, Q. Xin, and H. Liu, "Dynamic channel allocation for satellite internet of things via deep reinforcement learning," in 2020 International Conference on Information Networking (ICOIN), 2020, pp. 465–470.

[39] M. A. Qureshi, E. Lagunas, and G. Kaddoum, "Reinforcement learning for link adaptation and channel selection in leo satellite cognitive communications," IEEE Communications Letters, vol. 27, no. 3, pp. 951–955, 2023.

[40] G. Bersuker, M. Mason, and K. L. Jones, "Neuromorphic computing: The potential for high-performance processing in space," Game Changer, pp. 1–12, 2018.

[41] F. Ortiz, E. Lagunas, W. Martins, T. Dinh, N. Skatchkovsky, O. Simeone, B. Rajendran, T. Navarro, and S. Chatzinotas, "Towards the application of neuromorphic computing to satellite communications," in 39th International Communications Satellite Systems Conference (ICSSC). IEEE, 2022, pp. 1–7.

[42] F. de Guadalupe Ortíz Gómez, R. M. Rodríguez-Osorio, M. A. S. Natera, S. L. Ayala, D. Tarchi, and A. Vanelli-Coralli, "On the use of neural networks for flexible payload management in vhts systems," in 25th Ka Broadband Commun. Conf, 2019, pp. 1–10.

[43] Z. Lin, Z. Ni, L. Kuang, C. Jiang, and Z. Huang, "Dynamic beam pattern and bandwidth allocation based on multi-agent deep reinforcement learning for beam hopping satellite systems," IEEE Transactions on Vehicular Technology, vol. 71, no. 4, pp. 3917–3930, 2022.

[44] H. Nishiyama, D. Kudoh, N. Kato, and N. Kadowaki, "Load balancing and qos provisioning based on congestion prediction for geo/leo hybrid satellite networks," Proceedings of the IEEE, vol. 99, no. 11, pp. 1998–2007, 2011.

[45] A. Checko, H. L. Christiansen, Y. Yan, L. Scolari, G. Kardaras, M. S. Berger, and L. Dittmann, "Cloud ran for mobile networks—a technology overview," IEEE Communications Surveys & Tutorials, vol. 17, no. 1, pp. 405–426, 2015.

[46] A. Cornejo, S. Landeros-Ayala, J. M. Matias, and R. Martinez, "Applying learning methods to optimize the ground segment for hts systems," in 2020 IEEE 11th Latin American Symposium on Circuits & Systems (LASCAS), 2020, pp. 1–4.

[47] T. Mortlock and Z. M. Kassas, "Assessing machine learning for leo satellite orbit determination in simultaneous tracking and navigation," in 2021 IEEE Aerospace Conference (50100), 2021, pp. 1–8.

[48] X. He, K. Zhao, and X. Chu, "Automl: A survey of the state-of-the-art," Knowledge-Based Systems, vol. 212, p. 106622, 2021.

[49] N. Cheng, F. Lyu, W. Quan, C. Zhou, H. He, W. Shi, and X. Shen, "Space/aerial-assisted computing offloading for iot applications: A learning-based approach," IEEE Journal on Selected Areas in Communications, vol. 37, no. 5, pp. 1117–1129, 2019.

[50] S. Xu, X.-W. Wang, and M. Huang, "Software-defined next-generation satellite networks: Architecture, challenges, and solutions," IEEE Access, vol. 6, pp. 4027–4041, 2018.

[51] G. Furano, G. Meoni, A. Dunne, D. Moloney, V. Ferlet-Cavrois, A. Tavoularis, J. Byrne, L. Buckley, M. Psarakis, K.-O. Voss, and L. Fanucci, "Towards the use of artificial intelligence on the edge in space systems: Challenges and opportunities," IEEE Aerospace and Electronic Systems Magazine, vol. 35, no. 12, pp. 44–56, 2020.

[52] G. Furano, A. Tavoularis, and M. Rovatti, "Ai in space: Applications examples and challenges," in 2020 IEEE International Symposium on Defect and Fault Tolerance in VLSI and Nanotechnology Systems (DFT). IEEE, 2020, pp. 1–6.

[53] A.-H. M. Jallad and L. B. Mohammed, "Hardware support vector machine (svm) for satellite on-board applications," in 2014 NASA/ESA Conference on Adaptive Hardware and Systems (AHS). IEEE, 2014, pp. 256–261.

[54] G. Labrèche, D. Evans, D. Marszk, T. Mladenov, V. Shiradhonkar, T. Soto, and V. Zelenevskiy, "Ops-sat spacecraft autonomy with tensorflow lite, unsupervised learning, and online machine learning," in 2022 IEEE Aerospace Conference (AERO). IEEE, 2022, pp. 1–17.

[55] G. Giuffrida, L. Fanucci, G. Meoni, M. Batič, L. Buckley, A. Dunne, C. Van Dijk, M. Esposito, J. Hefele, N. Vercruyssen et al., "The ϕ-sat-1 mission: The first on-board deep neural network demonstrator for satellite earth observation," IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1–14, 2021.

[56] J. J. Garau Luis, "Robustness of reinforcement learning systems in real-world environments," Ph.D. dissertation, Massachusetts Institute of Technology, 2023.

[57] B. Xie, H. Cui, P. Cao, Y. He, and M. Guizani, "Computation offloading optimization in satellite-terrestrial integrated networks via offline deep reinforcement learning," IEEE Internet of Things Journal, 2024.

[58] S. Furman, T. Woods, C. Maracchion, and A. L. Drozd, "Offline reinforcement learning and cognitive radio resource management for space-based radio access network optimization," in 2023 IEEE Cognitive Communications for Aerospace Applications Workshop (CCAAW). IEEE, 2023, pp. 1–6.

[59] X. Liu, H. Zhang, K. Long, A. Nallanathan, and V. C. M. Leung, "Deep dyna-reinforcement learning based on random access control in LEO satellite IoT networks," IEEE Internet of Things Journal, vol. 9, no. 16, pp. 14 818–14 828, 2022.

[60] M. Plumridge, R. Marǻk, C. Ceccobello, P. Gómez, G. Meoni, F. Svoboda, and N. D. Lane, "Rapid distributed fine-tuning of a segmentation model onboard satellites," arXiv preprint arXiv:2411.17831, 2024.

[61] V. Růžička, G. Mateo-García, C. Bridges, C. Brunskill, C. Purcell, N. Longépé, and A. Markham, "Fast model inference and training on-board of satellites," in IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium, 2023, pp. 2002–2005.

[62] B. Xie, H. Cui, I. W.-H. Ho, Y. He, and M. Guizani, "Computation offloading and resource allocation in leo satellite-terrestrial integrated networks with system state delay," IEEE Transactions on Mobile Computing, 2024.

[63] Y. Omid, M. Aristodemou, S. Lambotharan, M. Derakhshani, and L. Hanzo, "Reinforcement learning-based downlink transmit precoding for mitigating the impact of delayed csi in satellite systems," arXiv preprint arXiv:2410.21489, 2024.

[64] C. Zhou, W. Wu, H. He, P. Yang, F. Lyu, N. Cheng, and X. Shen, "Deep reinforcement learning for delay-oriented iot task scheduling in sagin," IEEE Transactions on Wireless Communications, vol. 20, no. 2, pp. 911–925, 2021.

[65] Y. Zhao, A. Xiao, S. Wu, Y. Ou, C. Jiang, and L. Kuang, "Delay sensitive beam hopping for satellite communication systems relying on fully decentralized soft actor-critics," in 2023 International Conference on Wireless Communications and Signal Processing (WCSP). IEEE, 2023, pp. 707–712.

[66] S. Krishnan, B. Boroujerdian, W. Fu, A. Faust, and V. J. Reddi, "Air learning: a deep reinforcement learning gym for autonomous aerial robot visual navigation," Machine Learning, vol. 110, no. 9, pp. 2501–2540, 2021.

[67] B. Chen, M. Xu, L. Li, and D. Zhao, "Delay-aware model-based reinforcement learning for continuous control," Neurocomputing, vol. 450, pp. 119–128, 2021.

[68] T. V. Nguyen, H. D. Le, and A. T. Pham, "Adaptive rate/power control with ml-based channel prediction for op-

tical satellite systems," IEEE Transactions on Aerospace and Electronic Systems, 2024.

[69] M. Minardi, Y. Drif, T. X. Vu, I. Maity, C. Politis, and S. Chatzinotas, "SDN-based Testbed for Emerging Use Cases in Beyond 5G NTN-Terrestrial Networks," in 2nd International Workshop on Autonomous Network Management in 5G and Beyond Systems, Miami, FL, USA, May 2023, pp. 1–5.

[70] G. Mateo-Garcia, J. Veitch-Michaelis, L. Smith, S. V. Oprea, G. Schumann, Y. Gal, A. G. Baydin, and D. Backes, "Towards global flood mapping onboard low cost satellites with machine learning," Scientific reports, vol. 11, no. 1, pp. 1–12, 2021.

[71] "MLSAT | ESA TIA." [Online]. Available: https://artes.esa.int/projects/mlsat

[72] "The new space age: Ibm develops a unique, custom edge computing solution in space," https://www.ibm.com/cloud/blog/ibm-develops-a-unique-custom-edge-computing-solution-in-space.

[73] "Stream b: Research for revolutionary technology advancement towards 6g - smart networks," https://smart-networks.europa.eu/stream-b-research-for-revolutionary-technology-advancement-towards-6g/, fecha de acceso: 20-03-2023.

[74] "Objectives - atria," https://www.atria-h2020.eu/objectives/, fecha de acceso: 20-03-2023.

[75] "Dynasat," https://www.dynasat.eu/, fecha de acceso: 20-03-2023.

[76] C. A. Balanis, Antenna theory: analysis and design. John wiley & sons, 2015.

[77] R. L. Haupt, Antenna Arrays: A computational approach. Wiley-IEEE Press, 2010.

[78] Vásquez-Peralvo, J. Querol, F. Ortiz, J. L. Rios, E. Lagunas, V. Monzon Baeza, G. Fontanesi, L. M. Garces-Socorras, J. C. Merlano Duncan, and S. Chatzinotas, "Flexible beamforming for direct radiating arrays in satellite communications," submitted to IEEE Access, 2022.

[79] K.-B. Yu, "Adaptive beamforming for satellite communication with selective earth coverage and jammer nulling capability," IEEE Transactions on Signal Processing, vol. 44, no. 12, pp. 3162–3166, 1996.

[80] G. Kautz, "Phase-only shaped beam synthesis via technique of approximated beam addition," IEEE Transactions on Antennas and Propagation, vol. 47, no. 5, pp. 887–894, 1999.

[81] H. Schippers, J. Verpoorte, P. Jorna, A. Hulzinga, A. Meijerink, C. Roeloffzen, R. Heideman, A. Leinse, and M. Wintels, "Conformal phased array with beam forming for airborne satellite communication," in 2008 International ITG Workshop on Smart Antennas, 2008, pp. 343–350.

[82] K. Sherman, "Phased array shaped multi-beam optimization for leo satellite communications using a genetic algorithm," in Proceedings 2000 IEEE International Conference on Phased Array Systems and Technology (Cat. No.00TH8510), 2000, pp. 501–504.

[83] T.-B. Chen, Y.-L. Dong, Y.-C. Jiao, and F. Zhang, "Synthesis of circular antenna array using crossed particle swarm optimization algorithm," Journal of Electromagnetic Waves and Applications, vol. 20, no. 13, pp. 1785–1795, 2006.

[84] D. Boeringer and D. Werner, "Particle swarm optimization versus genetic algorithms for phased array synthesis," IEEE Transactions on Antennas and Propagation, vol. 52, no. 3, pp. 771–779, 2004.

[85] R. Webster, "A generalized hamming window," IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 26, no. 3, pp. 269–270, 1978.

[86] T. Taylor, "Design of line-source antennas for narrow beamwidth and low side lobes," Transactions of the IRE Professional Group on Antennas and Propagation, vol. 3, no. 1, pp. 16–28, 1955.

[87] R. B. Blackman and J. W. Tukey, "The measurement of power spectra from the point of view of communications engineering — part i," The Bell System Technical Journal, vol. 37, no. 1, pp. 185–282, 1958.

[88] C. Dolph, "A current distribution for broadside arrays which optimizes the relationship between beam width and side-lobe level," Proceedings of the IRE, vol. 34, no. 6, pp. 335–348, 1946.

[89] W. Li, X. Huang, and H. Leung, "Performance evaluation of digital beamforming strategies for satellite communications," IEEE Transactions on Aerospace and Electronic systems, vol. 40, no. 1, pp. 12–26, 2004.

[90] S. Bianco, P. Napoletano, A. Raimondi, M. Feo, G. Petraglia, and P. Vinetti, "AESA Adaptive Beamforming Using Deep Learning," in 2020 IEEE Radar Conference (RadarConf20). IEEE, 2020, pp. 1–6.

[91] A. J. Singh and M. Jayakumar, "Machine learning based digital beamforming for line-of-sight optimization in satcom on the move technology," in 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA). IEEE, 2020, pp. 422–427.

[92] R. Kumar and S. Arnon, "Dnn beamforming for leo satellite communication at sub-thz bands," Electronics, vol. 11, no. 23, p. 3937, 2022.

[93] J. A. Vásquez-Peralvo, J. Querol, E. Lagunas, F. Ortiz, L. M. Garcés-Socarrás, J. L. González-Rios, V. M. Baeza, and S. Chatzinotas, "Genetic algorithm-based beamforming in subarray architectures for geo satellites," in 2024 18th European Conference on Antennas and Propagation (EuCAP). IEEE, 2024, pp. 1–5.

[94] F. Ortiz, J. A. Vasquez-Peralvo, J. Querol, E. Lagunas, J. L. G. Rios, M. O. Mendonça, L. Garces, V. M. Baeza, and S. Chatzinotas, "Supervised learning based real-time adaptive beamforming on-board multibeam satellites," in 2024 18th European Conference on Antennas and Propagation (EuCAP). IEEE, 2024, pp. 1–5.

[95] Q. Zhao, Y. Hu, Z. Pang, and D. Ren, "Beam hopping for leo satellite:challenges and opportunities," in 2022 International Conference on Culture-Oriented Science and Technology (CoST), 2022, pp. 319–324.

[96] P. Angeletti, D. F. Prim, and R. Rinaldo, Beam Hopping in Multi-Beam Broadband Satellite Systems: System Performance and Payload Architecture Analysis. [Online]. Available: https://arc.aiaa.org/doi/abs/10.2514/6.2006-5376

[97] L. Lei, E. Lagunas, Y. Yuan, M. G. Kibria, S. Chatzinotas, and B. Ottersten, "Beam illumination pattern design in satellite networks: Learning and optimization for efficient beam hopping," IEEE Access, vol. 8, pp. 136 655–136 667, 2020.

[98] E. Lagunas, M. G. Kibria, H. Al-Hraishawi, N. Maturo, and S. Chatzinotas, "Precoded cluster hopping for multibeam GEO satellite communication systems," Frontiers in Signal Processing, vol. 1, p. 721682, 2021.

[99] J. Lei and M. A. Vazquez-Castro, "Multibeam satellite frequency/time duality study and capacity optimization," Journal of Communications and Networks, vol. 13, no. 5, pp. 472–480, 2011.

[100] R. Alegre-Godoy, N. Alagha, and M. A. Vázquez-Castro, "Offered capacity optimization mechanisms for multi-beam satellite systems," in 2012 IEEE International Conference on Communications (ICC). IEEE, 2012, pp. 3180–3184.

[101] L. Chen, V. N. Ha, E. Lagunas, L. Wu, S. Chatzinotas, and B. Ottersten, "The next generation of beam hopping satellite systems: Dynamic beam illumination with selective precoding," IEEE Transactions on Wireless Communications, pp. 1–1, 2022.

[102] V. N. Ha, T. T. Nguyen, E. Lagunas, J. C. M. Duncan, and S. Chatzinotas, "Geo payload power minimization: Joint precoding and beam hopping design," arXiv preprint arXiv:2208.10474, 2022.

[103] J. Tang, D. Bian, G. Li, J. Hu, and J. Cheng, "Optimization method of dynamic beam position for leo beam-hopping satellite communication systems," IEEE Access, vol. 9, pp. 57 578–57 588, 2021.

[104] Z. Lin, Z. Ni, L. Kuang, C. Jiang, and Z. Huang, "Multi-satellite beam hopping based on load balancing and interference avoidance for ngso satellite communication systems," IEEE Transactions on Communications, pp. 1–1, 2022.

[105] L. Lei, E. Lagunas, Y. Yuan, M. G. Kibria, S. Chatzinotas, and B. Ottersten, "Deep learning for beam hopping in multibeam satellite systems," in 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring). IEEE, 2020, pp. 1–5.

[106] X. Hu, Y. Zhang, X. Liao, Z. Liu, W. Wang, and F. M. Ghannouchi, "Dynamic beam hopping method based on multi-objective deep reinforcement learning for next generation satellite broadband systems," IEEE Transactions on Broadcasting, vol. 66, no. 3, pp. 630–646, 2020.

[107] E. Godino, L. Escolar, and A. P. Honold, Flexible Payload Operations of Satellite Communication Systems. [Online]. Available: https://arc.aiaa.org/doi/abs/10.2514/6.2018-2653

[108] F. d. G. Ortíz Gómez, R. Martínez Rodríguez-Osorio, M. A. Salas Natera, S. Landeros Ayala, D. Tarchi, and A. Vanelli Coralli, "On the use of neural networks for flexible payload management in vhts systems," 2019.

[109] K. An, T. Liang, X. Yan, Y. Li, and X. Qiao, "Power allocation in land mobile satellite systems: An energy-efficient perspective," IEEE Communications Letters, vol. 22, no. 7, pp. 1374–1377, 2018.

[110] T. Qi and Y. Wang, "Energy-efficient power allocation over multibeam satellite downlinks with imperfect csi," in 2015 International Conference on Wireless Communications & Signal Processing (WCSP), 2015, pp. 1–5.

[111] C. N. Efrem and A. D. Panagopoulos, "Dynamic energy-efficient power allocation in multibeam satellite systems," IEEE Wireless Communications Letters, vol. 9, no. 2, pp. 228–231, 2020.

[112] J. Choi and V. Chan, "Optimum power and beam allocation based on traffic demands and channel conditions over satellite downlinks," IEEE Transactions on Wireless Communications, vol. 4, no. 6, pp. 2983–2993, 2005.

[113] F. R. Durand and T. Abrão, "Power allocation in multibeam satellites based on particle swarm optimization," AEU - International Journal of Electronics and Communications, vol. 78, pp. 124–133, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1434841116303739

[114] A. I. Aravanis, B. Shankar M. R., P.-D. Arapoglou, G. Danoy, P. G. Cottis, and B. Ottersten, "Power allocation in multibeam satellite systems: A two-stage multi-objective optimization," IEEE Transactions on Wireless Communications, vol. 14, no. 6, pp. 3171–3182, 2015.

[115] S. Liu, Y. Fan, Y. Hu, D. Wang, L. Liu, and L. Gao, "Ag-dpa: Assignment game–based dynamic power allocation in multibeam satellite systems," International Journal of Satellite Communications and Networking, vol. 38, no. 1, pp. 74–83, 2020. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/sat.1310

[116] J. Lei and M. A. Vázquez-Castro, "Joint power and carrier allocation for the multibeam satellite downlink with individual sinr constraints," in 2010 IEEE International Conference on Communications, 2010, pp. 1–5.

[117] T. S. Abdu, S. Kisseleff, E. Lagunas, and S. Chatzinotas, "A low-complexity resource optimization technique for high throughput satellite," in 2021 17th International Symposium on Wireless Communication Systems (ISWCS), 2021, pp. 1–5.

[118] ——, "Power and bandwidth minimization for demand-aware geo satellite systems," in 2021 IEEE Global Communications Conference (GLOBECOM), 2021, pp. 1–6.

[119] ——, "Flexible resource optimization for geo multibeam satellite communication system," IEEE Transactions on Wireless Communications, vol. 20, no. 12, pp. 7888–7902, 2021.

[120] T. Ramírez, C. Mosquera, and N. Alagha, "Flexible user mapping for radio resource assignment in advanced satellite payloads," IEEE Transactions on Broadcasting, vol. 68, no. 3, pp. 723–739, 2022.

[121] G. Cocco, T. de Cola, M. Angelone, Z. Katona, and S. Erl, "Radio resource management optimization of flexible satellite payloads for dvb-s2 systems," IEEE Transactions on Broadcasting, vol. 64, no. 2, pp. 266–280, 2018.

[122] A. Paris, I. Del Portillo, B. Cameron, and E. Crawley, "A genetic algorithm for joint power and bandwidth allocation in multibeam satellite systems," in 2019 IEEE Aerospace Conference, 2019, pp. 1–15.

[123] F. de Guadalupe Ortíz Gómez, R. M. Rodríguez-Osorio, M. A. S. Natera, and S. L. Ayala, "On the use machine learning for flexible payload management in vhts systems," in Proceedings of 70th International Astronautical Congress 2019, 2019, pp. 1–6. [Online]. Available: https://oa.upm.es/64705/

[124] P. Zhang, X. Wang, Z. Ma, S. Liu, and J. Song, "An online power allocation algorithm based on deep reinforcement learning in multibeam satellite systems," International Journal of Satellite Communications and Networking, vol. 38, no. 5, pp. 450–461, 2020. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/sat.1352

[125] J. J. G. Luis, M. Guerster, I. del Portillo, E. Crawley, and B. Cameron, "Deep reinforcement learning for continuous power allocation in flexible high throughput satellites," in 2019 IEEE Cognitive Communications for Aerospace Applications Workshop (CCAAW), 2019, pp. 1–4.

[126] J. J. G. Luis, N. Pachler, M. Guerster, I. del Portillo, E. Crawley, and B. Cameron, "Artificial intelligence algorithms for power allocation in high throughput satellites: A comparison," in 2020 IEEE Aerospace Conference, 2020, pp. 1–15.

[127] G. Fontanesi, A. Zhu, M. Arvaneh, and H. Ahmadi, "A transfer learning approach for uav path design with connectivity outage constraint," IEEE Internet of Things Journal, 2022.

[128] A. Destounis and A. D. Panagopoulos, "Dynamic power allocation for broadband multi-beam satellite communication networks," IEEE Commun. Lett., vol. 15, no. 4, pp. 380–382, 2011.

[129] H. Fenech, S. Amos, A. Tomatis, and V. Soumpholphakdy, "High throughput satellite systems: An analytical approach," IEEE Transactions on Aerospace and Electronic Systems, vol. 51, no. 1, pp. 192–202, 2015.

[130] Y. Kawamoto, T. Kamei, M. Takahashi, N. Kato, A. Miura, and M. Toyoshima, "Flexible resource allocation with inter-beam interference in satellite communication systems with a digital channelizer," IEEE Transactions on Wireless Communications, vol. 19, no. 5, pp. 2934–2945, 2020.

[131] U. Park, H. W. Kim, D. S. Oh, and B. J. Ku, "Flexible bandwidth allocation scheme based on traffic demands and channel conditions for multi-beam satellite systems," in 2012 IEEE Vehicular Technology Conference (VTC Fall), 2012, pp. 1–5.

[132] H. Wang, A. Liu, X. Pan, and L. Jia, "Optimal bandwidth allocation for multi-spot-beam satellite communication systems," in Proceedings 2013 International Conference on Mechatronic Sciences, Electric Engineering and Computer (MEC), 2013, pp. 2794–2798.

[133] N. Pachler, J. J. G. Luis, M. Guerster, E. Crawley, and B. Cameron, "Allocating power and bandwidth in multibeam satellite systems using particle swarm optimization," in 2020 IEEE Aerospace Conference, 2020, pp. 1–11.

[134] B. S. Mysore, E. Lagunas, S. Chatzinotas, and B. Ottersten, "Precoding for satellite communications: Why, how and what next?" IEEE Communications Letters, vol. 25, no. 8, pp. 2453–2457, 2021.

[135] A. I. Perez-Neira, M. A. Vazquez, M. B. Shankar, S. Maleki, and S. Chatzinotas, "Signal processing for high-throughput satellites: Challenges in new interference-limited scenarios," IEEE Signal Processing Magazine, vol. 36, no. 4, pp. 112–131, 2019.

[136] S. Liu, X. Hu, and W. Wang, "Deep reinforcement learning based dynamic channel allocation algorithm in multibeam satellite systems," IEEE Access, vol. 6, pp. 15 733–15 742, 2018.

[137] B. Zhao, J. Liu, Z. Wei, and I. You, "A deep reinforcement learning based approach for energy-efficient channel allocation in satellite internet of things," IEEE Access, vol. 8, pp. 62 197–62 206, 2020.

[138] Y. He, B. Sheng, H. Yin, D. Yan, and Y. Zhang, "Multi-objective deep reinforcement learning based time-frequency resource allocation for multi-beam satellite communications," China Communications, vol. 19, no. 1, pp. 77–91, 2022.

[139] Z. Li, Z. Xie, and X. Liang, "Dynamic channel reservation strategy based on dqn algorithm for multi-service leo satellite communication system," IEEE Wireless Communications Letters, vol. 10, no. 4, pp. 770–774, 2021.

[140] D. Deng, C. Wang, M. Pang, and W. Wang, "Dynamic resource allocation with deep reinforcement learning in multibeam satellite communication," IEEE Wireless Communications Letters, pp. 1–1, 2022.

[141] X. Liao, X. Hu, Z. Liu, S. Ma, L. Xu, X. Li, W. Wang, and F. M. Ghannouchi, "Distributed intelligence: A verification for multi-agent drl-based multibeam satellite resource allocation," IEEE Communications Letters, vol. 24, no. 12, pp. 2785–2789, 2020.

[142] C. Han, A. Liu, L. Huo, H. Wang, and X. Liang, "A prediction-based resource matching scheme for rentable leo satellite communication network," IEEE Communications Letters, vol. 24, no. 2, pp. 414–417, 2020.

[143] X. Ding, L. Feng, Y. Zou, and G. Zhang, "Deep learning aided spectrum prediction for satellite communication systems," IEEE Transactions on Vehicular Technology, vol. 69, no. 12, pp. 16 314–16 319, 2020.

[144] P. V. R. Ferreira, R. Paffenroth, A. M. Wyglinski, T. M. Hackett, S. G. Bilén, R. C. Reinhart, and D. J. Mortensen, "Multiobjective reinforcement learning for cognitive satellite communications using deep neural network ensembles," IEEE Journal on Selected Areas in Communications, vol. 36, no. 5, pp. 1030–1041, 2018.

[145] T. S. Abdu, S. Kisseleff, L. Lei, E. Lagunas, J. Grotz, and S. Chatzinotas, "A deep learning based acceleration of complex satellite resource management problem," in 2022 30th European Signal Processing Conference (EUSIPCO), 2022, pp. 1092–1096.

[146] H. Al-Hraishawi, E. Lagunas, and S. Chatzinotas, "Traffic simulator for multibeam satellite communication systems," in 10th Advanced Satellite Multimedia Syst. Conf. and the 16th Signal Process. Space Commun. Workshop (ASMS/SPSC), Sep. 2020, pp. 1–8.

[147] F. G. Ortiz-Gomez, M. A. Salas-Natera, R. Martínez, and S. Landeros-Ayala, "Optimization in vhts satellite system design with irregular beam coverage for non-uniform traffic distribution," Remote Sensing, vol. 13, no. 13, 2021. [Online]. Available: https://www.mdpi.com/2072-4292/13/13/2642

[148] P. J. Honnaiah, N. Maturo, S. Chatzinotas, S. Kisseleff, and J. Krause, "Demand-based adaptive multi-beam pattern and footprint planning for high throughput geo satellite systems," IEEE Open Journal of the Communications Society, vol. 2, pp. 1526–1540, 2021.

[149] K. Rao, M. Cuchanski, and M. Tang, "Multiple beam antenna concepts for satellite communications," in Symposium on Antenna Technology and Applied Electromagnetics [ANTEM 1994]. IEEE, 1994, pp. 289–292.

[150] S. K. Rao, "Advanced antenna technologies for satellite communications payloads," IEEE Transactions on Antennas and Propagation, vol. 63, no. 4, pp. 1205–1217, 2015.

[151] M. Schneider, C. Hartwanger, and H. Wolf, "Antennas for multiple spot beam satellites," CEAS Space Journal, vol. 2, no. 1, pp. 59–66, 2011.

[152] K. Y. Jo, Satellite communications network design and analysis. Artech house, 2011.

[153] Y. Su, Y. Liu, Y. Zhou, J. Yuan, H. Cao, and J. Shi, "Broadband leo satellite communications: Architectures and key technologies," IEEE Wireless Communications, vol. 26, no. 2, pp. 55–61, 2019.

[154] M. Takahashi, Y. Kawamoto, N. Kato, A. Miura, and M. Toyoshima, "Adaptive power resource allocation with multi-beam directivity control in high-throughput satellite communication systems," IEEE Wireless Communications Letters, vol. 8, no. 4, pp. 1248–1251, 2019.

[155] S. Tani, K. Motoyoshi, H. Sano, A. Okamura, H. Nishiyama, and N. Kato, "An adaptive beam control technique for q band satellite to maximize diversity gain and mitigate interference to terrestrial networks," IEEE Transactions on Emerging Topics in Computing, vol. 7, no. 1, pp. 115–122, 2016.

[156] S. Kisseleff, B. Shankar, D. Spano, and J.-D. Gayrard, "A new optimization tool for mega-constellation design and its application to trunking systems [international communications satellite systems conference]," 2019.

[157] F. G. Ortiz-Gomez, D. Tarchi, R. Martínez, A. Vanelli-Coralli, M. A. Salas-Natera, and S. Landeros-Ayala, "Cooperative multi-agent deep reinforcement learning for resource management in full flexible vhts systems," IEEE Transactions on Cognitive Communications and Networking, vol. 8, no. 1, pp. 335–349, 2022.

[158] G. Dalal, K. Dvijotham, M. Vecerik, T. Hester, C. Paduraru, and Y. Tassa, "Safe exploration in continuous action spaces," arXiv preprint arXiv:1801.08757, 2018.

[159] P. V. R. Ferreira, R. Paffenroth, A. M. Wyglinski, T. M. Hackett, S. G. Bilen, R. C. Reinhart, and D. J. Mortensen, "Reinforcement learning for satellite communications: From leo to deep space operations," IEEE Communications Magazine, vol. 57, no. 5, pp. 70–75, 2019.

[160] H. He, W. Yuan, Y. Hou, S. Chen, X. Jiang, R. Zhu, and J. Yang, "Onboard processing aided transmission delay minimization for leo satellite networks," IEEE Transactions on Communications, 2024.

[161] A. Almamori and S. Mohan, "A spectrally efficient algorithm for massive MIMO for mitigating pilot contamination," in 2017 IEEE 38th Sarnoff Symposium, Newark, NJ, USA, Sep. 2017, pp. 1–5.

[162] A. Pérez-Neira, J. M. Veciana, M. Á. Vázquez, and E. Lagunas, "Distributed power control with received power constraints for time-area-spectrum licenses," Signal Processing, vol. 120, pp. 141–155, 2016.

[163] E. Lagunas, S. Maleki, S. Chatzinotas, M. Soltanalian, A. I. Pérez-Neira, and B. Oftersten, "Power and rate allocation in cognitive satellite uplink networks," in 2016 IEEE International Conference on Communications (ICC). IEEE, 2016, pp. 1–6.

[164] D. Chen, J. Zhang, and R. Zhao, "Adaptive modulation and coding in satellite-integrated 5g communication system," in 2021 IEEE 21st International Conference on Communication Technology (ICCT), 2021, pp. 1402–1407.

[165] E. İnceöz, R. Tutgun, and A. M. Y. Turgut, "Fpga based transmitter design using adaptive coding and modulation schemes for low earth orbit satellite communications," in 2020 IEEE 5th International Symposium on Telecommunication Technologies (ISTT), 2020, pp. 39–44.

[166] J. Bas and A. A. Dowhuszko, "Time-packing as enabler of optical feeder link adaptation in high throughput satellite systems," in 2020 IEEE 3rd 5G World Forum (5GWF), 2020, pp. 186–192.

[167] S. Andrenacci, D. Spano, D. Christopoulos, S. Chatzinotas, J. Krause, and B. Ottersten, "Optimized link adaptation for dvb-s2x precoded waveforms based on snir estimation," in 2016 50th Asilomar Conference on Signals, Systems and Computers, 2016, pp. 502–506.

[168] A. Tsakmalis, S. Chatzinotas, and B. Ottersten, "Interference constraint active learning with uncertain feedback for cognitive radio networks," IEEE Transactions on Wireless Communications, vol. 16, no. 7, pp. 4654–4668, 2017.

[169] L. Pellaco, V. Saxena, M. Bengtsson, and J. Jaldén, "Wireless link adaptation with outdated csi — a hybrid data-driven and model-based approach," in 2020 IEEE 21st International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), 2020, pp. 1–5.

[170] X. Wang, H. Li, and Q. Wu, "Optimizing adaptive coding and modulation for satellite network with ml-based csi prediction," in 2019 IEEE Wireless Communications and Networking Conference (WCNC), 2019, pp. 1–6.

[171] D. Lee, Y. G. Sun, I. Sim, J.-H. Kim, Y. Shin, D. I. Kim, and J. Y. Kim, "Neural episodic control-based adaptive modulation and coding scheme for inter-satellite communication link," IEEE Access, vol. 9, pp. 159 175–159 186, 2021.

[172] J. Ebert, W. Bailer, J. Flavio, K. Plimon, and M. Winter, "A method for acm on q/v-band satellite links based on artificial intelligence," in 2020 10th Advanced Satellite Multimedia Systems Conference and the 16th Signal Processing for Space Communications Workshop (ASMS/SPSC), 2020, pp. 1–5.

[173] J. Zou, H. Xiong, D. Wang, and C. W. Chen, "Optimal power allocation for hybrid overlay/underlay spectrum sharing in multiband cognitive radio networks," IEEE Trans. Veh. Commun., vol. 62, no. 4, pp. 1827–1837, 2013.

[174] S. K. Sharma, S. Chatzinotas, and B. Ottersten, "In-line Interference Mitigation Techniques for Spectral Coexistence of GEO and NGEO Satellites," Int. J. Satell. Commun. Network, vol. 34, no. 1, pp. 11–39, 2016.

[175] K. Kim, I. A. Akbar, K. K. Bae, J.-S. Um, C. M. Spooner, and J. H. Reed, "Cyclostationary Approaches to Signal Detection and Classification in Cognitive Radio," in 2007 2nd IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, 2007, pp. 212–215.

[176] I. Jabandžić, F. Firyaguna, S. Giannoulis, A. Shahid, A. Mukhopadhyay, M. Ruffini, and I. Moerman, "The codysun approach: A novel distributed paradigm for dynamic spectrum sharing in satellite communications," Sensors, vol. 21, no. 23, 2021. [Online]. Available: https://www.mdpi.com/1424-8220/21/23/8052

[177] W. Qin and F. Dovis, "Situational awareness of chirp jamming threats to gnss based on supervised machine learning," IEEE

Trans. Aerosp. Electron. Syst., vol. 58, no. 3, pp. 1707–1720, 2022.

[178] P. Henarejos, M. A. Vazquez, and A. I. Perez-Neira, "Deep learning for experimental hybrid terrestrial and satellite interference management," in 2019 IEEE 20th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), 2019, pp. 1–5.

[179] M. Kulin, T. Kazaz, I. Moerman, and E. De Poorter, "End-to-End Learning From Spectrum Data: A Deep Learning Approach for Wireless Signal Identification in Spectrum Monitoring Applications," IEEE Access, vol. 6, pp. 18 484–18 501, 2018.

[180] Y. Wang, C. Zhang, Q. Peng, and Z. Wang, "Learning to detect frame synchronization," in Neural Information Processing, M. Lee, A. Hirose, Z.-G. Hou, and R. M. Kil, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 570–578.

[181] H. Wu, Z. Sun, and X. Zhou, "Deep learning-based frame and timing synchronization for end-to-end communications," Journal of Physics: Conference Series, vol. 1169, pp. 012–060, Feb 2019.

[182] J. Wang, W. Tu, L. C. K. Hui, S. M. Yiu, and E. K. Wang, "Detecting time synchronization attacks in cyber-physical systems with machine learning techniques," in 2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS), 2017, pp. 2246–2251.

[183] S. Lee, S. Kim, M. Seo, and D. Har, "Synchronization of frequency hopping by lstm network for satellite communication system," IEEE Communications Letters, vol. 23, no. 11, pp. 2054–2058, 2019.

[184] D. Zibar, L. H. H. de Carvalho, M. Piels, A. Doberstein, J. Diniz, B. Nebendahl, C. Franciscangelis, J. Estaran, H. Haisch, N. G. Gonzalez, J. C. R. F. de Oliveira, and I. T. Monroy, "Application of machine learning techniques for amplitude and phase noise characterization," Journal of Lightwave Technology, vol. 33, no. 7, pp. 1333–1343, 2015.

[185] J. Tong, R. Song, Y. Liu, C. Wang, Q. Zhou, and W. Wang, "Enhanced synchronization of 5g integrated satellite systems in multipath channels," in 2020 International Conference on Computer Vision, Image and Deep Learning (CVIDL), 2020, pp. 617–621.

[186] V.-P. Bui, T. Van Chien, E. Lagunas, J. Grotz, S. Chatzinotas, and B. Ottersten, "Robust congestion control for demand-based optimization in precoded multi-beam high throughput satellite communications," IEEE Transactions on Communications, vol. 70, no. 10, pp. 6918–6937, 2022.

[187] L. Bai, Q. Xu, S. Wu, S. Ventouras, and G. Goussetis, "A Novel Atmosphere-Informed Data-Driven Predictive Channel Modeling for B5G/6G Satellite-Terrestrial Wireless Communication Systems at Q-Band," IEEE Transactions on Vehicular Technology, vol. 69, no. 12, pp. 14 225–14 237, 2020.

[188] L. Bai, C.-X. Wang, Q. Xu, S. Ventouras, and G. Goussetis, "Prediction of Channel Excess Attenuation for Satellite Communication Systems at Q-Band Using Artificial Neural Network," IEEE Antennas and Wireless Propagation Letters, vol. 18, no. 11, pp. 2235–2239, 2019.

[189] A. Cornejo, S. Landeros-Ayala, J. M. Matias, F. Ortiz-Gomez, R. Martinez, and M. Salas-Natera, "Method of Rain Attenuation Prediction Based on Long–Short Term Memory Network," Neural Processing Letters, vol. 54, no. 4, pp. 2959–2995, 2022.

[190] A. Ferdowsi and D. Whitefield, "Deep Learning for Rain Fade Prediction in Satellite Communications," in 2021 IEEE Globecom Workshops (GC Wkshps), 2021, pp. 1–6.

[191] M. Á. Vázquez, A. Perez-Neira, D. Christopoulos, S. Chatzinotas, B. Ottersten, P.-D. Arapoglou, A. Ginesi, and G. Taricco, "Precoding in multibeam satellite communications: Present and future challenges," IEEE Wireless Communications, vol. 23, no. 6, pp. 88–95, 2016.

[192] R. Hunger, Floating point operations in matrix-vector calculus. Munich University of Technology, Inst. for Circuit Theory and Signal Processing, 2005.

[193] M. Van de Kamp, "Short-term prediction of rain attenuation using two samples," Electronics Letters, vol. 38, no. 23, p. 1, 2002.

[194] L. De Montera, C. Mallet, L. Barthès, and P. Golé, "Short-term prediction of rain attenuation level and volatility in Earth-to-Satellite links at EHF band," Nonlinear Processes in Geophysics, vol. 15, no. 4, pp. 631–643, 2008.

[195] T. Maseng and P. Bakken, "A Stochastic Dynamic Model of Rain Attenuation," IEEE Transactions on Communications, vol. 29, no. 5, pp. 660–669, 1981.

[196] N. Jeannin, L. Castanet, I. Dahman, V. Pourret, and B. Pouponneau, "Smart gateways switching control algorithms based on tropospheric propagation forecasts," International Journal of Satellite Communications and Networking, vol. 37, no. 1, pp. 43–55, 2019.

[197] C. Huang, R. He, B. Ai, A. F. Molisch, B. K. Lau, K. Haneda, B. Liu, C.-X. Wang, M. Yang, C. Oestges, and Z. Zhong, "Artificial Intelligence Enabled Radio Propagation for Communications—Part I: Channel Characterization and Antenna-Channel Optimization," IEEE Transactions on Antennas and Propagation, vol. 70, no. 6, pp. 3939–3954, 2022.

[198] M. A. Vázquez, P. Henarejos, and L. Blanco, "Deep Gateway Switching," in 2022 27th Ka and Broadband Communications Conference (Ka) and the 39th International Communications Satellite Systems Conference (ICSSC), 2012.

[199] P. Hailes, L. Xu, R. G. Maunder, B. M. Al-Hashimi, and L. Hanzo, "A survey of fpga-based ldpc decoders," IEEE Communications Surveys & Tutorials, vol. 18, no. 2, pp. 1098–1122, 2016.

[200] M. Y. Zinchenko, A. M. Levadniy, and Y. A. Grebenko, "Ldpc decoder power consumption optimization," in 2020 International Youth Conference on Radio Electronics, Electrical and Power Engineering (REEPE), 2020, pp. 1–5.

[201] J. Kang, J. S. An, and B. Wang, "An efficient fec encoder core for vcm leo satellite-ground communications," IEEE Access, vol. 8, pp. 125 692–125 701, 2020.

[202] V. Pignoly, B. Le Gal, C. Jego, B. Gadat, and L. Barthe, "Fair comparison of hardware and software ldpc decoder implementations for sdr space links," in 2020 27th IEEE International Conference on Electronics, Circuits and Systems (ICECS), 2020, pp. 1–4.

[203] K. Niu, J. Dai, K. Tan, and J. Gao, "Deep learning methods for channel decoding: A brief tutorial," in 2021 IEEE/CIC International Conference on Communications in China (ICCC), 2021, pp. 144–149.

[204] E. Nachmani, Y. Be'ery, and D. Burshtein, "Learning to decode linear codes using deep learning," in 2016 54th Annual Allerton Conference on Communication, Control, and Computing (Allerton), 2016, pp. 341–346.

[205] N. Agrawal, "Machine intelligence in decoding of forward error correction codes." Ph.D. dissertation, 10 2017.

[206] L. Lugosch, Learning Algorithms for Error Correction, ser. McGill theses. McGill University Libraries, 2018. [Online]. Available: https://books.google.es/books?id=EyANugEACAAJ

[207] A. Haroon, F. Hussain, and M. R. Bajwa, "Decoding of error correcting codes using neural networks," 2013.

[208] P. Henarejos and M. Ángel Vázquez, "Decoding 5g-nr communications via deep learning," in ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, pp. 3782–3786.

[209] L. Pellaco, M. Bengtsson, and J. Jaldén, "Matrix-inverse-free deep unfolding of the weighted mmse beamforming algorithm," IEEE Open Journal of the Communications Society, vol. 3, pp. 65–81, 2022.

[210] T. Yoo and A. Goldsmith, "On the optimality of multiantenna broadcast scheduling using zero-forcing beamforming," IEEE Journal on Selected Areas in Communications, vol. 24, no. 3, pp. 528–541, 2006.

[211] P. Viswanath, D. Tse, and R. Laroia, "Opportunistic beamforming using dumb antennas," IEEE Transactions on Information Theory, vol. 48, no. 6, pp. 1277–1294, 2002.

[212] A. Guidotti and A. Vanelli-Coralli, "Geographical scheduling for multicast precoding in multi-beam satellite systems," in 2018 9th Advanced Satellite Multimedia Systems Conference and the 15th Signal Processing for Space Communications Workshop (ASMS/SPSC), 2018, pp. 1–8.

[213] G. Taricco, "Linear precoding methods for multi-beam broadband satellite systems," in European Wireless 2014; 20th European Wireless Conference, 2014, pp. 1–6.

[214] V. Joroughi, M. A. Vázquez, and A. I. Pérez-Neira, "Generalized multicast multibeam precoding for satellite commu-

nications," IEEE Transactions on Wireless Communications, vol. 16, no. 2, pp. 952–966, 2016.

[215] M. Á. Vázquez, M. R. B. Shankar, C. I. Kourogiorgas, P.-D. Arapoglou, V. Icolari, S. Chatzinotas, A. D. Panagopoulos, and A. I. Pérez-Neira, "Precoding, Scheduling, and Link Adaptation in Mobile Interactive Multibeam Satellite Systems," IEEE Journal on Selected Areas in Communications, vol. 36, no. 5, pp. 971–980, 2018.

[216] Z. Sha, Z. Wang, S. Chen, and L. Hanzo, "Graph theory based beam scheduling for inter-cell interference avoidance in mmwave cellular networks," IEEE Transactions on Vehicular Technology, vol. 69, no. 4, pp. 3929–3942, 2020.

[217] S. Dimitrov, S. Erl, B. Barth, S. Jaeckel, A. Kyrgiazos, and B. G. Evans, "Radio resource management techniques for high throughput satellite communication systems," in 2015 European Conference on Networks and Communications (EuCNC). IEEE, 2015, pp. 175–179.

[218] S. Zhang, M. Jia, Y. Wei, and Q. Guo, "User scheduling for multicast transmission in high throughput satellite systems," EURASIP Journal on Wireless Communications and Networking, vol. 2020, no. 1, p. 133, Jun 2020. [Online]. Available: https://doi.org/10.1186/s13638-020-01749-7

[219] D. Christopoulos, S. Chatzinotas, and B. Ottersten, "Multicast multigroup precoding and user scheduling for frame-based satellite communications," IEEE Trans. Wireless Commun, vol. 14, p. 9, September 2015.

[220] P. J. Honnaiah, E. Lagunas, S. Chatzinotas, and J. Krause, "Interference-aware demand-based user scheduling in precoded high throughput satellite systems," IEEE Open Journal of Vehicular Technology, vol. 3, pp. 120–137, 2022.

[221] Y. D. Zhang and K. D. Pham, "Joint precoding and scheduling optimization in downlink multicell satellite communications," in 2020 54th Asilomar Conference on Signals, Systems, and Computers, 2020, pp. 480–484.

[222] A. Bandi, B. S. Mysore R., S. Chatzinotas, and B. Ottersten, "Joint scheduling and precoding for frame-based multigroup multicasting in satellite communications," in 2019 IEEE Global Communications Conference (GLOBECOM), 2019, pp. 1–6.

[223] A. Bandi, B. Shankar M. R, S. Chatzinotas, and B. Ottersten, "A joint solution for scheduling and precoding in multiuser MISO downlink channels," IEEE Transactions on Wireless Communications, vol. 19, no. 1, pp. 475–490, 2020.

[224] A. Guidotti and A. Vanelli-Coralli, "Clustering strategies for multicast precoding in multibeam satellite systems," International Journal of Satellite Communications and Networking, vol. 38, no. 2, pp. 85–104, 2020. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/sat.1312

[225] F. Ortiz, E. Lagunas, and S. Chatzinotas, "Unsupervised learning for user scheduling in multibeam precoded geo satellite systems," in 2022 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit), 2022, pp. 190–195.

[226] ——, "Unsupervised learning for user scheduling in multibeam precoded geo satellite systems," in 2022 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit). IEEE, 2022, pp. 190–195.

[227] Y. Chi, L. Liu, G. Song, C. Yuen, Y. L. Guan, and Y. Li, "Practical mimo-noma: Low complexity and capacity-approaching solution," IEEE Transactions on Wireless Communications, vol. 17, no. 9, pp. 6251–6264, 2018.

[228] L. Liu, C. Yuen, Y. L. Guan, and Y. Li, "Capacity-achieving iterative lmmse detection for mimo-noma systems," in 2016 IEEE International Conference on Communications (ICC), 2016, pp. 1–6.

[229] L. Liu, Y. Chi, C. Yuen, Y. L. Guan, and Y. Li, "Capacity-achieving mimo-noma: Iterative lmmse detection," IEEE Transactions on Signal Processing, vol. 67, no. 7, pp. 1758–1773, 2019.

[230] J. Jiao, Y. Sun, S. Wu, Y. Wang, and Q. Zhang, "Network utility maximization resource allocation for noma in satellite-based internet of things," IEEE Internet of Things Journal, vol. 7, no. 4, pp. 3230–3242, 2020.

[231] B. Makki, K. Chitti, A. Behravan, and M.-S. Alouini, "A survey of noma: Current status and open research challenges," IEEE Open Journal of the Communications Society, vol. 1, pp. 179–189, 2020.

[232] J. Zhao, X. Yue, S. Kang, and W. Tang, "Joint effects of imperfect csi and sic on noma based satellite-terrestrial systems," IEEE Access, vol. 9, pp. 12 545–12 554, 2021.

[233] S. Xie, B. Zhang, D. Guo, and W. Ma, "Outage performance of noma-based integrated satellite-terrestrial networks with imperfect csi," Electronics Letters, vol. 55, no. 14, pp. 793–795, 2019. [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/el.2018.7839

[234] V. Andiappan and V. Ponnusamy, "Deep learning enhanced noma system: A survey on future scope and challenges," Wireless Personal Communications, vol. 123, no. 1, pp. 839–877, Mar 2022. [Online]. Available: https://doi.org/10.1007/s11277-021-09160-1

[235] X. Yan, K. An, Q. Zhang, G. Zheng, S. Chatzinotas, and J. Han, "Delay constrained resource allocation for NOMA enabled satellite internet of things with deep reinforcement learning," IEEE Internet of Things Journal, 2020.

[236] A. Wang, L. Lei, E. Lagunas, S. Chatzinotas, and B. Ottersten, "Dual-dnn assisted optimization for efficient resource scheduling in noma-enabled satellite systems," in 2021 IEEE Global Communications Conference (GLOBECOM), 2021, pp. 1–6.

[237] Q. Liu, J. Jiao, S. Wu, R. Lu, and Q. Zhang, "Deep reinforcement learning-assisted noma age-optimal power allocation for s-iot network," in ICC 2022 - IEEE International Conference on Communications, 2022, pp. 1823–1828.

[238] Y. Sun, Y. Wang, J. Jiao, S. Wu, and Q. Zhang, "Deep learning-based long-term power allocation scheme for NOMA downlink system in S-IoT," IEEE Access, vol. 7, pp. 86 288–86 296, 2019.

[239] J. Luo, J. Tang, D. K. C. So, G. Chen, K. Cumanan, and J. A. Chambers, "A deep learning-based approach to power minimization in multi-carrier noma with swipt," IEEE Access, vol. 7, pp. 17 450–17 460, 2019.

[240] A. Wang, L. Lei, E. Lagunas, S. Chatzinotas, and B. Ottersten, "Completion time minimization in noma systems: Learning for combinatorial optimization," IEEE Networking Letters, vol. 3, no. 1, pp. 15–18, 2021.

[241] X. Yan, K. An, C.-X. Wang, W.-P. Zhu, Y. Li, and Z. Feng, "Genetic algorithm optimized support vector machine in noma-based satellite networks with imperfect csi," in ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, pp. 8817–8821.

[242] Y. Mao, B. Clerckx, and V. O. Li, "Rate-splitting multiple access for downlink communication systems: bridging, generalizing, and outperforming sdma and noma," EURASIP Journal on Wireless Communications and Networking, vol. 2018, no. 1, p. 133, May 2018. [Online]. Available: https://doi.org/10.1186/s13638-018-1104-7

[243] ——, "Energy efficiency of rate-splitting multiple access, and performance benefits over sdma and noma," in 2018 15th International Symposium on Wireless Communication Systems (ISWCS), 2018, pp. 1–5.

[244] B. Clerckx, Y. Mao, E. Jorswieck, J. Yuan, D. Love, E. Erkip, and D. Niyato, "A primer on rate-splitting multiple access: Tutorial, myths, and frequently asked questions," 09 2022.

[245] S. Gamal, M. Rihan, S. Hussin, A. Zaghloul, and A. A. Salem, "Multiple access in cognitive radio networks: From orthogonal and non-orthogonal to rate-splitting," IEEE Access, vol. 9, pp. 95 569–95 584, 2021.

[246] L. Yin and B. Clerckx, "Rate-splitting multiple access for multigroup multicast and multibeam satellite systems," IEEE Transactions on Communications, vol. 69, no. 2, pp. 976–990, 2020.

[247] ——, "Rate-splitting multiple access for multibeam satellite communications," in 2020 IEEE International Conference on Communications Workshops (ICC Workshops), 2020, pp. 1–6.

[248] Z. W. Si, L. Yin, and B. Clerckx, "Rate-splitting multiple access for multigateway multibeam satellite systems with feeder link interference," IEEE Transactions on Communications, vol. 70, no. 3, pp. 2147–2162, 2022.

[249] X. Li, Y. Fan, R. Yao, P. Wang, N. Qi, N. I. Miridakis, and T. A. Tsiftsis, "Rate-splitting multiple access-enabled security analysis in cognitive satellite terrestrial networks," IEEE Transactions on Vehicular Technology, vol. 71, no. 11, pp. 11 756–11 771, 2022.

[250] Q. Zhang and L. Zhu, "A deep learning approach for downlink sum rate maximization in satellite-terrestrial integrated

network," in 2022 International Symposium on Networks, Computers and Communications (ISNCC), 2022, pp. 1–5.

[251] Q. Zhang, L. Zhu, S. Jiang, and X. Tang, "Deep unfolding for cooperative rate splitting multiple access in hybrid satellite terrestrial networks," China Communications, vol. 19, no. 7, pp. 100–109, 2022.

[252] J. Huang, Y. Yang, L. Yin, D. He, and Q. Yan, "Deep reinforcement learning-based power allocation for rate-splitting multiple access in 6g leo satellite communication system," IEEE Wireless Communications Letters, vol. 11, no. 10, pp. 2185–2189, 2022.

[253] A. Vanelli-Coralli, A. Guidotti, T. Foggi, G. Colavolpe, and G. Montorsi, "5g and beyond 5g non-terrestrial networks: trends and research challenges," in 2020 IEEE 3rd 5G World Forum (5GWF), 2020, pp. 163–169.

[254] M. Werner, C. Delucchi, H.-J. Vogel, G. Maral, and J.-J. De Ridder, "Atm-based routing in leo/meo satellite networks with intersatellite links," IEEE Journal on Selected Areas in Communications, vol. 15, no. 1, pp. 69–82, 1997.

[255] G. Stock, J. A. Fraire, and H. Hermanns, "Distributed on-demand routing for leo mega-constellations: A starlink case study," in 2022 11th Advanced Satellite Multimedia Systems Conference and the 17th Signal Processing for Space Communications Workshop (ASMS/SPSC), 2022, pp. 1–8.

[256] N. Razmi, B. Matthiesen, A. Dekorsy, and P. Popovski, "On-board federated learning for dense leo constellations," in ICC 2022 - IEEE International Conference on Communications, 2022, pp. 4715–4720.

[257] C. Qiu, H. Yao, F. R. Yu, F. Xu, and C. Zhao, "Deep q-learning aided networking, caching, and computing resources allocation in software-defined satellite-terrestrial networks," IEEE Transactions on Vehicular Technology, vol. 68, no. 6, pp. 5871–5883, 2019.

[258] N. Kato, Z. M. Fadlullah, F. Tang, B. Mao, S. Tani, A. Okamura, and J. Liu, "Optimizing space-air-ground integrated networks by artificial intelligence," IEEE Wireless Communications, vol. 26, no. 4, pp. 140–147, 2019.

[259] A. Cigliano and F. Zampognaro, "A machine learning approach for routing in satellite mega-constellations," in 2020 International Symposium on Advanced Electrical and Communication Technologies (ISAECT), 2020, pp. 1–6.

[260] D. A. Tubiana, J. Farhat, G. Brante, and R. D. Souza, "Q-learning NOMA random access for IoT-satellite terrestrial relay networks," IEEE Wireless Communications Letters, vol. 11, no. 8, pp. 1619–1623, 2022.

[261] O. Liberg, S. E. Löwenmark, S. Euler, B. Hofström, T. Khan, X. Lin, and J. Sedin, "Narrowband internet of things for non-terrestrial networks," IEEE Communications Standards Magazine, vol. 4, no. 4, pp. 49–55, 2020.

[262] R. De Gaudenzi, O. Del Rio Herrero, G. Gallinaro, S. Cioni, and P. Arapoglou, "Random access schemes for satellite networks, from VSAT to M2M: a survey," International journal of satellite communications and networking, vol. 36, no. 1, pp. 66–107, 2018.

[263] C. Kissling and A. M. Dlr, "On the integration of random access and DAMA channels for the return link of satellite networks," in 2013 IEEE International Conference on Communications (ICC), 2013, pp. 4282–4287.

[264] R. De Gaudenzi and O. del Rio Herrero, "Advances in random access protocols for satellite networks," in 2009 International Workshop on Satellite and Space Communications, 2009, pp. 331–336.

[265] B. Zhao, G. Ren, X. Dong, and H. Zhang, "Distributed q-learning based joint relay selection and access control scheme for iot-oriented satellite terrestrial relay networks," IEEE Communications Letters, vol. 25, no. 6, pp. 1901–1905, 2021.

[266] M. V. da Silva, R. D. Souza, H. Alves, and T. Abrão, "A noma-based q-learning random access method for machine type communications," IEEE Wireless Communications Letters, vol. 9, no. 10, pp. 1720–1724, 2020.

[267] D. Zhou, M. Sheng, Y. Wang, J. Li, and Z. Han, "Machine learning-based resource allocation in satellite networks supporting internet of remote things," IEEE Transactions on Wireless Communications, vol. 20, no. 10, pp. 6606–6621, 2021.

[268] D. de la Torre, F. G. Ortiz-Gomez, M. Salas-Natera, and R. Martínez, "Analysis of the traffic demand on very high throughput satellite for 5g," in Proceedings of the XXXV Simposio Nacional de la Unión Científica Internacional de Radio (URSI 2020), Malaga, Spain, 2020, pp. 2–4.

[269] J. Wu, Y. Peng, M. Song, M. Cui, and L. Zhang, "Link congestion prediction using machine learning for software-defined-network data plane," in 2019 International Conference on Computer, Information and Telecommunication Systems (CITS). IEEE, 2019, pp. 1–5.

[270] Y. Li, R. Yu, C. Shahabi, and Y. Liu, "Diffusion convolutional recurrent neural network: Data-driven traffic forecasting," in International Conference on Learning Representations (ICLR '18), 2018.

[271] L. Lei, Y. Yuan, T. X. Vu, S. Chatzinotas, M. Minardi, and J. F. M. Montoya, "Dynamic-adaptive ai solutions for network slicing management in satellite-integrated b5g systems," IEEE Network, vol. 35, no. 6, pp. 91–97, 2021.

[272] T. K. Rodrigues and N. Kato, "Network slicing with centralized and distributed reinforcement learning for combined satellite/ground networks in a 6g environment," vol. 29, no. 1, pp. 104–110, conference Name: IEEE Wireless Communications.

[273] I. Bisio, F. Lavagetto, G. Verardo, and T. de Cola, "Network slicing optimization for integrated 5g-satellite networks," in 2019 IEEE Global Communications Conference (GLOBECOM), pp. 1–6, ISSN: 2576-6813.

[274] H. Linder, H. Clausen, and B. Collini-Nocker, "Satellite internet services using dvb/mpeg-2 and multicast web caching," IEEE Communications Magazine, vol. 38, no. 6, pp. 156–161, 2000.

[275] C. Brinton, E. Aryafar, S. Corda, S. Russo, R. Reinoso, and M. Chiang, "An intelligent satellite multicast and caching overlay for cdns to improve performance in video applications," in Proc. AIAA Int. Commun. Satellite Syst. Conf., 2013, pp. 386–391.

[276] S. Semanjski, A. Muls, I. Semanjski, and W. De Wilde, "Use and validation of supervised machine learning approach for detection of GNSS signal spoofing," in 2019 International Conference on Localization and GNSS (ICL-GNSS), Jun. 2019, pp. 1–6.

[277] F. Gallardo and A. P. Yuste, "SCER spoofing attacks on the Galileo open service and machine learning techniques for end-user protection," IEEE Access, vol. 8, pp. 85 515–85 532, 2020.

[278] S. Semanjski, I. Semanjski, W. De Wilde, and A. Muls, "Use of supervised machine learning for GNSS signal spoofing detection with validation on real-world meaconing and spoofing data—part i," Sensors, vol. 20, no. 4, Feb. 2020.

[279] Q. Wu, C. Feres, D. Kuzmenko, D. Zhi, Z. Yu, X. Liu, and X. 'Leo' Liu, "Deep learning based RF fingerprinting for device identification and wireless security," Electron. Lett., vol. 54, no. 24, pp. 1405–1407, Nov. 2018.

[280] N. Soltanieh, Y. Norouzi, Y. Yang, and N. C. Karmakar, "A review of radio frequency fingerprinting techniques," IEEE J. Radio Freq. Identification, vol. 4, no. 3, pp. 222–233, Jan. 2020.

[281] T. Jian, B. C. Rendon, E. Ojuba, N. Soltani, Z. Wang, K. Sankhe, A. Gritsenko, J. Dy, K. Chowdhury, and S. Ioannidis, "Deep learning for rf fingerprinting: A massive experimental study," IEEE Internet Things Mag., vol. 3, no. 1, pp. 50–57, Mar. 2020.

[282] J.-Y. Liu, H.-J. Ding, C.-M. Zhang, S.-P. Xie, and Q. Wang, "Practical phase-modulation stabilization in quantum key distribution via machine learning," Phys. Rev. Applied, vol. 12, p. 014059, Jul. 2019.

[283] W. Wang and H.-K. Lo, "Machine learning for optimal parameter prediction in quantum key distribution," Phys. Rev. A, vol. 100, p. 062334, Dec. 2019.

[284] Z.-A. Ren, Y.-P. Chen, J.-Y. Liu, H.-J. Ding, and Q. Wang, "Implementation of machine learning in quantum key distributions," IEEE Commun. Lett., vol. 25, no. 3, pp. 940–944, Mar. 2021.

[285] 3GPP, "System architecture for the 5G System (5GS)," 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 23.501, 12 2021, version 17.3.0. [Online]. Available: http://www.3gpp.org/DynaReport/23501.htm

[286] ——, "Management and orchestration; Concepts, use cases and requirements," 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 28.530, 12 2021, version 17.2.0. [Online]. Available: http://www.3gpp.org/DynaReport/28530.htm

[287] B. Tiomela Jou, O. Vidal, P. Foulon, D. Pham-Minh, I. Keesmaat, M. Boutin, S. Watts, C. Politis, K. Liolis, R. Sperber, P. S. Khodashenas, and L. Goratti, "Integrated SaT5g general network architecture," issue: D3.1. [Online]. Available: https://www.sat5g-project.eu/wp-content/uploads/2019/04/SaT5G-D3.1-Integrated-SaT5G-general-network-architecture_ADS_v1.00_Inter....pdf

[288] VITAL consortium. H2020 VITAL project. [Online]. Available: http://www.ict-vital.eu/

[289] B. T. Jou, O. Vidal, J. Cahill, F. Arnal, L.-M. Honssin, M. Boutin, and D. K. Chau, "Architecture options for satellite integration into 5g networks," in 2018 European Conference on Networks and Communications (EuCNC), pp. 398–9, ISSN: 2575-4912.

[290] T. Ahmed, A. Alleg, R. Ferrus, and R. Riggio, "On-demand network slicing using SDN/NFV-enabled satellite ground segment systems," in 2018 4th IEEE Conference on Network Softwarization and Workshops (NetSoft), pp. 242–246.

[291] Y. Drif, E. Chaput, E. Lavinal, P. Berthou, B. Tiomela Jou, O. Gremillet, and F. Arnal, "An extensible network slicing framework for satellite integration into 5g," International Journal of Satellite Communications and Networking, vol. 39, no. 4, pp. 339–357, 2021.

[292] Y. Drif, E. Lavinal, E. Chaput, P. Berthou, B. T. Jou, O. Grémillet, and F. Arnal, "Slice aware non terrestrial networks," in 2021 IEEE 46th Conference on Local Computer Networks (LCN), 2021, pp. 24–31.

[293] O. Kodheli, A. Guidotti, and A. Vanelli-Coralli, "Integration of satellites in 5g through leo constellations," in GLOBECOM 2017 - 2017 IEEE Global Communications Conference, 2017, pp. 1–6.

[294] O. Kodheli, A. Astro, J. Querol, M. Gholamian, S. Kumar, N. Maturo, and S. Chatzinotas, "Random access procedure over non-terrestrial networks: From theory to practice," vol. 9, pp. 109 130–109 143, conference Name: IEEE Access.

[295] P. Mach and Z. Becvar, "Mobile edge computing: A survey on architecture and computation offloading," IEEE Communications Surveys & Tutorials, vol. 19, no. 3, pp. 1628–1656, 2017.

[296] S. Wang, X. Zhang, Y. Zhang, L. Wang, J. Yang, and W. Wang, "A survey on mobile edge networks: Convergence of computing, caching and communications," IEEE Access, vol. 5, pp. 6757–6779, 2017.

[297] L. Breslau, P. Cao, L. Fan, G. Phillips, and S. Shenker, "Web caching and zipf-like distributions: evidence and implications," in IEEE INFOCOM '99. Conference on Computer Communications. Proceedings. Eighteenth Annual Joint Conference of the IEEE Computer and Communications Societies. The Future is Now (Cat. No.99CH36320), vol. 1, 1999, pp. 126–134 vol.1.

[298] Z. Zhang, W. Zhang, and F.-H. Tseng, "Satellite mobile edge computing: Improving qos of high-speed satellite-terrestrial networks using edge computing techniques," IEEE Network, vol. 33, no. 1, pp. 70–76, 2019.

[299] Pierluigi Paganini. (2015, Aug.) Hacking the Iridium network could be very easy. Security Affairs. [Online]. Available: https://securityaffairs.co/wordpress/39510/hacking/hacking-iridium-network.html

[300] Z. Wu, Y. Zhang, Y. Yang, C. Liang, and R. Liu, "Spoofing and anti-spoofing technologies of global navigation satellite system: A survey," IEEE Access, vol. 8, pp. 165 444–165 496, 2020.

[301] P. Yue, J. An, J. Zhang, G. Pan, S. Wang, P. Xiao, and L. Hanzo, "On the security of LEO satellite communication systems: Vulnerabilities, countermeasures, and future trends," arXiv preprint arXiv:2201.03063, Jan. 2022.

[302] W. Akoto. (2020, Feb.) Hackers could shut down satellites—or turn them into weapons. The Conversation. [Online]. Available: https://theconversation.com/hackers-could-shut-down-satellites-or-turn-them-into-weapons-130932

[303] N. Rodríguez-Barroso, D. Jiménez-López, M. V. Luzón, F. Herrera, and E. Martínez-Cámara, "Survey on federated learning threats: Concepts, taxonomy on attacks and defences, experimental study and challenges," Inf. Fusion, vol. 90, pp. 148–173, Feb. 2023.

[304] H. Cruickshank, "A security system for satellite networks," in Proc. Fifth Satellite Systems for Mobile Commun. and Navigation. IET, May 1996, pp. 187–190.

[305] M.-S. Hwang, C.-C. Yang, and C.-Y. Shiu, "An authentication scheme for mobile satellite communication systems," SIGOPS Oper. Syst. Rev., vol. 37, no. 4, p. 42–47, Oct. 2003.

[306] X. Deng, J. Shao, L. Chang, and J. Liang, "A blockchain-based authentication protocol using cryptocurrency technology in LEO satellite networks," Electronics, vol. 10, no. 24, 2021.

[307] E. Jedermann, M. Strohmeier, M. Schäfer, J. Schmitt, and V. Lenders, "Orbit-based authentication using tdoa signatures in satellite networks," in Proceedings of the 14th ACM Conference on Security and Privacy in Wireless and Mobile Networks, 2021, p. 175–180.

[308] Y. Liu, L. Ni, and M. Peng, "A secure and efficient authentication protocol for satellite-terrestrial networks," IEEE Internet Things J., 2022, early access.

[309] H. Fang, X. Wang, and S. Tomasin, "Machine learning for intelligent authentication in 5G and beyond wireless networks," IEEE Wireless Commun., vol. 26, no. 5, pp. 55–61, Oct. 2019.

[310] W. M. Mahmoud, D. Elfiky, S. M. Robaa, M. S. Elnawawy, and S. M. Yousef, "Effect of atomic Oxygen on LEO cubesat," Int. J. Aeronaut. Space Sci., vol. 22, no. 3, pp. 726–733, Jun. 2021.

[311] S. Qiu, K. Sava, and W. Guo, "Robust satellite antenna fingerprinting under degradation using recurrent neural network," Mod. Phys. Lett. B, vol. 36, no. 12, p. 2250043, Apr. 2022.

[312] C. Jiang, X. Wang, J. Wang, H.-H. Chen, and Y. Ren, "Security in space information networks," IEEE Commun. Mag., vol. 53, no. 8, pp. 82–88, Aug. 2015.

[313] S. Lohani and R. Joshi, "Satellite network security," in 2020 International Conference on Emerging Trends in Communication, Control and Computing (ICONC3), Feb. 2020, pp. 1–5.

[314] J. Ma, R. Shrestha, J. Adelberg, C.-Y. Yeh, Z. Hossain, E. Knightly, J. M. Jornet, and D. M. Mittleman, "Security and eavesdropping in terahertz wireless links," Nature, vol. 563, no. 7729, pp. 89–93, Nov. 2018.

[315] B. Li, Z. Fei, C. Zhou, and Y. Zhang, "Physical-layer security in space information networks: A survey," IEEE Internet Things J., vol. 7, no. 1, pp. 33–52, Sep. 2020.

[316] Y. Huang, J. Wang, C. Zhong, T. Q. Duong, and G. K. Karagiannidis, "Secure transmission in cooperative relaying networks with multiple antennas," IEEE Trans. Wireless Commun., vol. 15, no. 10, pp. 6843–6856, Jul. 2016.

[317] N. Zhao, F. R. Yu, M. Li, Q. Yan, and V. C. M. Leung, "Physical layer security issues in interference- alignment-based wireless networks," IEEE Commun. Mag., vol. 54, no. 8, pp. 162–168, Aug. 2016.

[318] M. G. Schraml, A. Knopp, and K.-U. Storek, "Multi-user MIMO satellite communications with secrecy constraints," in MILCOM 2019 - 2019 IEEE Military Communications Conference (MILCOM), Nov. 2019, pp. 17–22.

[319] M. G. Schraml, R. T. Schwarz, and A. Knopp, "Multiuser MIMO concept for physical layer security in multibeam satellite systems," IEEE Trans. Inf. Forensics Security, vol. 16, pp. 1670–1680, Nov. 2021.

[320] C. Gidney and M. Ekerå, "How to factor 2048 bit RSA integers in 8 hours using 20 million noisy qubits," Quantum, vol. 5, p. 433, Apr. 2021.

[321] C. H. Bennett and G. Brassard, "Quantum cryptography: Public key distribution and coin tossing," in Proceedings of IEEE International Conference on Computers, Systems, and Signal Processing, Bangalore, India. New York: IEEE, Dec. 1984, pp. 175–179.

[322] A. K. Ekert, "Quantum cryptography based on Bell's theorem," Phys. Rev. Lett., vol. 67, pp. 661–663, Aug. 1991.

[323] H.-K. Lo, M. Curty, and B. Qi, "Measurement-device-independent quantum key distribution," Phys. Rev. Lett., vol. 108, p. 130503, Mar 2012.

[324] R. Renner, "Security of quantum key distribution," Ph.D. dissertation, Swiss Federal Institute of Technology, Zurich, Switzerland, 2005.

[325] M. Curty, F. Xu, W. Cui, C. C. W. Lim, K. Tamaki, and H.-K. Lo, "Finite-key analysis for measurement-device-independent quantum key distribution," Nat. Commun., vol. 5, Apr. 2014.

[326] M. Tomamichel, C. C. W. Lim, N. Gisin, and R. Renner, "Tight finite-key analysis for quantum cryptography," Nat. Commun., vol. 3, p. 634, Jan. 2012.

[327] R. Renner and R. Wolf, "Quantum advantage in cryptography," arXiv preprint arxiv:2206.04078, 2022.

[328] J. ur Rehman, Y. Jeong, and H. Shin, "Quantum key distribution with a control key," in 2017 Int. Symp. Wireless Commun. Systems (ISWCS), Aug. 2017, pp. 112–116.

[329] J. ur Rehman, S. Qaisar, Y. Jeong, and H. Shin, "Security of a control key in quantum key distribution," Mod. Phys. Lett. B, vol. 31, no. 11, p. 1750119, Apr. 2017.

[330] S.-K. Liao, W.-Q. Cai, W.-Y. Liu, L. Zhang, Y. Li, J.-G. Ren, J. Yin, Q. Shen, Y. Cao, Z.-P. Li, F.-Z. Li, X.-W. Chen, L.-H. Sun, J.-J. Jia, J.-C. Wu, X.-J. Jiang, J.-F. Wang, Y.-M. Huang, Q. Wang, Y.-L. Zhou, L. Deng, T. Xi, L. Ma, T. Hu, Q. Zhang, Y.-A. Chen, N.-L. Liu, X.-B. Wang, Z.-C. Zhu, C.-Y. Lu, R. Shu, C.-Z. Peng, J.-Y. Wang, and J.-W. Pan, "Satellite-to-ground quantum key distribution," Nature, vol. 549, no. 7670, pp. 43–47, Sep. 2017.

[331] S.-K. Liao, W.-Q. Cai, J. Handsteiner, B. Liu, J. Yin, L. Zhang, D. Rauch, M. Fink, J.-G. Ren, W.-Y. Liu, Y. Li, Q. Shen, Y. Cao, F.-Z. Li, J.-F. Wang, Y.-M. Huang, L. Deng, T. Xi, L. Ma, T. Hu, L. Li, N.-L. Liu, F. Koidl, P. Wang, Y.-A. Chen, X.-B. Wang, M. Steindorfer, G. Kirchner, C.-Y. Lu, R. Shu, R. Ursin, T. Scheidl, C.-Z. Peng, J.-Y. Wang, A. Zeilinger, and J.-W. Pan, "Satellite-relayed intercontinental quantum network," Phys. Rev. Lett., vol. 120, p. 030501, Jan. 2018.

[332] S. Pirandola, "Satellite quantum communications: Fundamental bounds and practical security," Physical Review Research, vol. 3, no. 2, p. 023130, 2021.

[333] S. Wang, W. Chen, Z.-Q. Yin, D.-Y. He, C. Hui, P.-L. Hao, G.-J. Fan-Yuan, C. Wang, L.-J. Zhang, J. Kuang, S.-F. Liu, Z. Zhou, Y.-G. Wang, G.-C. Guo, and Z.-F. Han, "Practical gigahertz quantum key distribution robust against channel disturbance," Opt. Lett., vol. 43, no. 9, pp. 2030–2033, May 2018.

[334] H.-M. Chin, N. Jain, D. Zibar, U. L. Andersen, and T. Gehring, "Machine learning aided carrier recovery in continuous-variable quantum key distribution," npj Quantum Inf., vol. 7, no. 1, p. 20, Feb 2021.

[335] H. Choi and S. Pack, "Cooperative downloading for leo satellite networks: A drl-based approach," Sensors, vol. 22, no. 18, p. 6853, 2022.

[336] L. Dalin, W. Haijiao, Y. Zhen, G. Yanfeng, and S. Shi, "An online distributed satellite cooperative observation scheduling algorithm based on multiagent deep reinforcement learning," IEEE Geoscience and Remote Sensing Letters, vol. 18, no. 11, pp. 1901–1905, 2020.

[337] R. Deng, B. Di, H. Zhang, L. Kuang, and L. Song, "Ultra-dense leo satellite constellations: How many leo satellites do we need?" IEEE Transactions on Wireless Communications, vol. 20, no. 8, pp. 4843–4857, 2021.

[338] R. Radhakrishnan, W. W. Edmonson, F. Afghah, R. M. Rodriguez-Osorio, F. Pinto, and S. C. Burleigh, "Survey of inter-satellite communication for small satellite systems: Physical layer to network layer view," IEEE Communications Surveys & Tutorials, vol. 18, no. 4, pp. 2442–2473, 2016.

[339] B. Palmintier, C. Kitts, P. Stang, and M. Swartwout, "A distributed computing architecture for small satellite and multi-spacecraft missions," 2002.

[340] SmartSat, "Machine learning onboard satellites," SmartSat Technical Report no. 010, SmartSat, Adelaide, Australia, Tech. Rep., 2021.

[341] G. Ghiasi, T.-Y. Lin, and Q. V. Le, "Nas-fpn: Learning scalable feature pyramid architecture for object detection," in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019, pp. 7036–7045.

[342] V. Monzon Baeza, F. Ortiz, E. Lagunas, T. S. Abdu, and S. Chatzinotas, "Gateway station geographical planning for emerging non-geostationary satellites constellations," IEEE Network, vol. 38, no. 4, pp. 158–165, 2024.

[343] Y. Abe, F. Ortiz, E. Lagunas, V. M. Baeza, S. Chatzinotas, and H. Tsuji, "Optimizing satellite network infrastructure: A joint approach to gateway placement and routing," in 2024 IEEE 99th Vehicular Technology Conference (VTC2024-Spring), 2024, pp. 1–6.

[344] I. del Portillo Barrios, B. Cameron, and E. Crawley, "Ground segment architectures for large leo constellations with feeder links in ehf-bands," 03 2018, pp. 1–14.

[345] E. Juan, M. Lauridsen, J. Wigard, and P. E. Mogensen, "5g new radio mobility performance in leo-based non-terrestrial networks," in 2020 IEEE Globecom Workshops (GC Wkshps, 2020, pp. 1–6.

[346] N. K. Lyras, C. N. Efrem, C. I. Kourogiorgas, A. D. Panagopoulos, and P.-D. Arapoglou, "Optimizing the ground network of optical meo satellite communication systems," IEEE Systems Journal, vol. 14, no. 3, pp. 3968–3976, 2020.

[347] N. Torkzaban, A. Gholami, J. S. Baras, and C. Papagianni, "Joint satellite gateway placement and routing for integrated satellite-terrestrial networks," in ICC 2020 - 2020 IEEE International Conference on Communications (ICC), 2020, pp. 1–6.

[348] A. Alvaro, L. Pascual, A. Abad, P. Pinto, A. Alvarez-Herrero, T. Belenguer, C. Miravet, P. Campo, L. F. Rodriguez, M. Reyes, J. Socas, and J. Bermejo, "Caramuel: The future of space quantum key distribution in geo," in 2022 IEEE International Conference on Space Optical Systems and Applications (ICSOS), 2022, pp. 57–65.

[349] C. N. Efrem and A. D. Panagopoulos, "Globally optimal selection of ground stations in satellite systems with site diversity," IEEE Wireless Communications Letters, vol. 9, no. 7, pp. 1101–1104, 2020.

[350] H. Dahrouj, R. Alghamdi, H. Alwazani, S. Bahanshal, A. A. Ahmad, A. Faisal, R. Shalabi, R. Alhadrami, A. Subasi, M. T. Al-Nory, O. Kittaneh, and J. S. Shamma, "An overview of machine learning-based techniques for solving optimization problems in communications and signal processing," IEEE Access, vol. 9, pp. 74 908–74 938, 2021.

[351] K. Çelikbilek, Z. Saleem, R. Morales Ferre, J. Praks, and E. S. Lohan, "Survey on optimization methods for leo-satellite-based networks with applications in future autonomous transportation," Sensors, vol. 22, no. 4, 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/4/1421

[352] S. C. Cripps, RF power amplifiers for wireless communications. Artech house Norwood, MA, 2006, vol. 2.

[353] E. McCune, "Chapter 3 - transmitter linearity and energy efficiency," in Linearization and Efficiency Enhancement Techniques for Silicon Power Amplifiers, E. Kerhervé and D. Belot, Eds. Oxford: Academic Press, 2015, pp. 55–81. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780124186781000039

[354] T. Kobal, Y. Li, X. Wang, and A. Zhu, "Digital predistortion of rf power amplifiers with phase-gated recurrent neural networks," IEEE Transactions on Microwave Theory and Techniques, 2022.

[355] Y. Zhang, Y. Li, F. Liu, and A. Zhu, "Vector decomposition based time-delay neural network behavioral model for digital predistortion of rf power amplifiers," IEEE Access, vol. 7, pp. 91 559–91 568, 2019.

[356] X. Chen, Z. Lu, S. Zhang, S. Xu, and Y. Wang, "An intermodulation oriented learning based digital pre-distortion technique via joint intermediate and radio frequency optimization," IEEE Transactions on Wireless Communications, 2022.

[357] L. Sun, P. Chu, and R. Zhu, "Navigation signal radio frequency channel modeling and predistortion technology based on artificial intelligence technology and neural network," Mobile Information Systems, vol. 2022, 2022.

[358] M. S. Elbamby, C. Perfecto, C.-F. Liu, J. Park, S. Samarakoon, X. Chen, and M. Bennis, "Wireless edge computing with latency and reliability guarantees," Proceedings of the IEEE, vol. 107, no. 8, pp. 1717–1737, 2019.

[359] E. Lagunas, F. Ortiz, G. Eappen, S. Daoud, W. A. Martins, J. Querol, S. Chatzinotas, N. Skatchkovsky, B. Rajendran, and O. Simeone, "Performance evaluation of neuromorphic hardware for onboard satellite communication applications," arXiv preprint arXiv:2401.06911, 2024.

[360] AMD Inc., "First space-grade Versal AI Core devices to ship early 2023," p. 1, nov 2022. [Online]. Available: https://www.amd.com/en/press-releases/2022-11-15-amd-announces\-completion-class-b-qualification-for-first-space-grade

[361] G. Pang, "The AI Chip Race," IEEE Intelligent Systems, vol. 37, no. 2, pp. 111–112, 2022, accessed: 2022-9.

[362] I. Rodriguez, L. Kosmidis, O. Notebaert, F. J. Cazorla, and D. Steenari, "An On-board Algorithm Implementation on an Embedded GPU: A Space Case Study," in Design, Automation and Test in Europe Conference and Exhibition, DATE 2020. Grenoble, France: Institute of Electrical and Electronics Engineers Inc., mar 2020, pp. 1718–1719.

[363] AMD XILINX Inc., "Versal Architecture and Product Data Sheet: Overview," AMD XILINX Inc., San Jose, CA, Data Sheet, nov 2022.
[364] NVIDIA Corp., "NVIDIA Jetson AGX Orin Series," Tech. Rep., mar 2022. [Online]. Available: http://ci.nii.ac.jp/naid/40005137127/
[365] AMD XILINX Inc., "AI Inference with Versal AI Core Series," AMD XILINX Inc., San Jose, CA, Tech. Rep., 2022.
[366] AMD Inc., "AMD Instinct MI200 Series Accelerator," AMD Inc., AMD Inc., Tech. Rep., 2021.
[367] ——, "AMD Instinct MI210 Accelerator," AMD Inc., AMD Inc., Tech. Rep., 2022.
[368] Qualcomm, "Qualcomm Cloud AI 100 Purpose-built for high performance, low-power AI processing in the cloud." Qualcomm Technologies Inc., Tech. Rep., 2020.
[369] ——, "Qualcomm Cloud AI 100 Edge Development Kit," Qualcomm Technologies Inc., Product Brief, 2020. [Online]. Available: https://www.qualcomm.com/products/cloud-artificial-intelligence/cloud-ai
[370] ——, "Qualcomm Cloud AI 100 MLPerf v2.0 Inference Benchmarks," Qualcomm Technologies Inc., Tech. Rep., 2022.
[371] NVIDIA Corp., "NVIDIA Jetson Orin NX Series," NVIDIA Corp., Datasheet, 2022. [Online]. Available: http://www.papersearch.net/view/detail.asp?detail{_}key=10000715
[372] LUXonis, "BW1099EMB - Myriad X SoM," Datasheet, nov 2020.
[373] NVIDIA Corp., "NVIDIA Jetson Roadmap," p. 1, 2022. [Online]. Available: https://developer.nvidia.com/embedded/develop/roadmap
[374] ——, "NVIDIA Jetson TX2 NX System-on-Module," NVIDIA Corp., Tech. Rep., mar 2022.
[375] ——, "NVIDIA Jetson Xavier NX Series System-on-Module," NVIDIA Corp., Datasheet, 2021. [Online]. Available: https://developer.nvidia.com/embedded/downloads
[376] ——, "NVIDIA Jetson AGX Xavier Series System-on-Module," Datasheet, 2021.
[377] ——, "NVIDIA Jetson Orin Nano Series," NVIDIA Corp., Datasheet, 2022. [Online]. Available: http://www.papersearch.net/view/detail.asp?detail{_}key=10000715
[378] ——, "Introducing Jetson Orin Nano," 2022. [Online]. Available: https://www.nvidia.com/en-us/autonomous-machines/embedded-systems/jetson-orin/
[379] AMD XILINX Inc., "Versal ACAP AI Edge Series," AMD XILINX Inc., Product Selection Guide, 2022. [Online]. Available: https://docs.xilinx.com/v/u/en-US/versal-ai-edge-product-selection-guide
[380] XILINX Inc., "AI Core Series Versal ™ AI Core Series Product Selection Guide," XILINX Inc., Product Selection Guide, 2019.
[381] iWave Systems, "Versal AI Edge/Prime SOM - iWave Systems," p. 1, 2023. [Online]. Available: https://www.iwavesystems.com/product/versal-ai-edge-system-on-module/
[382] T. electronic, "TE0950 AMD Versal™ AI Edge Evaluation board," https://shop.trenz-electronic.de/en/TE0950-02-EGBE21A-AMD-Versal-AI-Edge-Evalboard-with-VE2302-FLSIZE-8-GB-DDR4-SDRAM-15x12-cm/, p. 1, 2023.
[383] HiTech Global, "Xilinx Versal Prime/AI board," p. 1, 2022. [Online]. Available: http://www.hitechglobal.com/Boards/VERSAL{_}PCIE.htm
[384] AMD XILINX Inc., "Versal AI Core Series VCK190 Evaluation Kit," p. 1, 2021. [Online]. Available: https://www.xilinx.com/products/boards-and-kits/vck190.html
[385] I. . ©BrainChip, "Akida brainchip." [Online]. Available: https://brainchip.com/akida-neural-processor-soc/
[386] F. Akopyan, J. Sawada, A. Cassidy, R. Alvarez-Icaza, J. Arthur, P. Merolla, N. Imam, Y. Nakamura, P. Datta, G.-J. Nam, B. Taba, M. Beakes, B. Brezzo, J. B. Kuang, R. Manohar, W. P. Risk, B. Jackson, and D. S. Modha, "Truenorth: Design and tool flow of a 65 mw 1 million neuron programmable neurosynaptic chip," IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, vol. 34, no. 10, pp. 1537–1557, 2015.
[387] M. Davies, N. Srinivasa, T. Lin, G. Chinya, Y. Cao, S. H. Choday, G. Dimou, P. Joshi, N. Imam, S. Jain, Y. Liao, C. Lin, A. Lines, R. Liu, D. Mathaikutty, S. McCoy, A. Paul, J. Tse, G. Venkataramanan, Y. Weng, A. Wild, Y. Yang, and H. Wang, "Loihi: A Neuromorphic Manycore Processor with On-Chip Learning," IEEE Micro, vol. 38, no. 1, pp. 82–99, Jan 2018.
[388] "Introducing Qualcomm Zeroth Processors: Brain-Inspired Computing | Qualcomm." [Online]. Available: https://www.qualcomm.com/news/onq/2013/10/10/introducing-qualcomm-zeroth-processors-brain-inspired-computing
[389] S. Furber and P. Bogdan, Eds., SpiNNaker - A spiking neural network architecture, ser. NowOpen. Hanover, MD: now, Mar. 2020.
[390] J. Schemmel, A. Grübl, S. Hartmann, A. Kononov, C. Mayr, K. Meier, S. Millner, J. Partzsch, S. Schiefer, S. Scholze, R. Schüffny, and M.-O. Schwartz, "Live demonstration: A scaled-down version of the brainscales wafer-scale neuromorphic system," in 2012 IEEE International Symposium on Circuits and Systems (ISCAS), 2012, pp. 702–702.
[391] B. V. Benjamin, P. Gao, E. McQuinn, S. Choudhary, A. R. Chandrasekaran, J.-M. Bussat, R. Alvarez-Icaza, J. V. Arthur, P. A. Merolla, and K. Boahen, "Neurogrid: A mixed-analog-digital multichip system for large-scale neural simulations," Proceedings of the IEEE, vol. 102, no. 5, pp. 699–716, 2014.
[392] A. Neckar, S. Fok, B. V. Benjamin, T. C. Stewart, N. N. Oza, A. R. Voelker, C. Eliasmith, R. Manohar, and K. Boahen, "Braindrop: A mixed-signal neuromorphic architecture with a dynamical systems-based programming model," Proceedings of the IEEE, vol. 107, no. 1, pp. 144–164, 2019.
[393] S. Moradi, N. Qiao, F. Stefanini, and G. Indiveri, "A scalable multicore architecture with heterogeneous memory structures for dynamic neuromorphic asynchronous processors (dynaps)," IEEE Transactions on Biomedical Circuits and Systems, vol. 12, no. 1, pp. 106–122, 2018.
[394] C. Frenkel, M. Lefebvre, J.-D. Legat, and D. Bol, "A 0.086-mm^2 12.7-pj/sop 64k-synapse 256-neuron online-learning digital spiking neuromorphic processor in 28-nm cmos," IEEE Transactions on Biomedical Circuits and Systems, vol. 13, no. 1, pp. 145–158, 2019.
[395] F. Ortiz, N. Skatchkovsky, E. Lagunas, W. A. Martins, G. Eappen, S. Daoud, O. Simeone, B. Rajendran, and S. Chatzinotas, "Energy-efficient on-board radio resource management for satellite communications via neuromorphic computing," IEEE Transactions on Machine Learning in Communications and Networking, vol. 2, pp. 169–189, 2024.
[396] European Space Agency, "Satellite Signal Processing Techniques using a Commercial Off-The-Shelf AI Chipset (SPAICE)," p. 1, 2022. [Online]. Available: https://connectivity.esa.int/projects/spaice
[397] L. M. Garcés-Socarrás, A. Nik, F. Ortiz, J. A. Vásquez-Peralvo, J. L. Gonzalez, M. Chehailty, M. Kuhfuss, E. Lagunas, J. Thoemel, S. Kumar, V. Singh, J. C. Duncan, S. Malmir, S. Varadajulu, J. Querol, and S. Chatzinotas, "Artificial Intelligence Satellite Telecommunication Testbed using Commercial Off-The-Shelf Chipsets," in The First Joint European Space Agency / IAA Conference on AI in and for Space (SPAICE2024), D. Dold, A. Hadjiivanov, and D. Izzo, Eds. ESA European Centre for Space Applications and Telecommunications (ECSAT). Harwell, UK: European Space Agency (ESA), sep 2024, pp. 169–174. [Online]. Available: https://zenodo.org/records/13885551
[398] L. Kosmidis, I. Rodríguez, Á. Jover, S. Alcaide, J. Lachaize, J. Abella, O. Notebaert, F. J. Cazorla, and D. Steenari, "GPU4S (GPUs for Space): Are we there yet?" in European Workshop on On-Board Data Processing (OBDP), ESA, Ed. Online: ESA, jun 2021, pp. 1–8. [Online]. Available: https://atpi.eventsair.com/QuickEventWebsitePortal/obdp-2021/website/Agenda/AgendaItemDetail?id=c719851f-003e-47ad-81ca-0255dcd1f651
[399] D. Steenari, K. Forster, D. O'Callaghan, M. Tali, C. Hay, M. Cebecauer, M. Ireland, S. McBerren, and R. Camarero, "Survey of High-Performance Processors and FPGAs for On-Board Processing and Machine Learning Applications," in European Workshop on On-Board Data Processing (OBDP), ESA, Ed. Online: ESA, jun 2021, p. 28. [Online]. Available: https://atpi.eventsair.com/QuickEventWebsitePortal/obdp-2021/website/Agenda/AgendaItemDetail?id=1dea8c4d-04a0-4f40-8d9c-2bee77a904d7
[400] R. Ginosar, D. Goldfeld, P. Aviely, R. Golan, A. Meir, F. Lange, D. Alon, T. Liran, and A. Shabtai, "Ramon Space

RC64-based AI/ML Inference Engine," in European Workshop on On-Board Data Processing (OBDP), jun 2021, pp. 1–33. [Online]. Available: https://zenodo.org/record/5521124

[401] I. Rodriguez, L. Kosmidis, J. Lachaize, O. Notebaert, and D. Steenari, "Design and Implementation of an Open GPU Benchmarking Suite for Space Payload Processing," Universitat Politecnica de Catalunya, pp. 1–6, 2019.

[402] D. Steenari, L. Kosmidis, I. Rodriquez-Ferrandez, A. Jover-Alvarez, and K. Forster, "OBPMark (On-Board Processing Benchmarks) - Open Source Computational Performance Benchmarks for Space Applications," in European Workshop on On-Board Data Processing (OBDP), ESA, Ed. On-line: ESA, jun 2021, pp. 14–17. [Online]. Available: https://atpi.eventsair.com/QuickEventWebsitePortal/obdp-2021/website

[403] L. Kosmidis, J. Lachaize, J. Abella, O. Notebaert, F. J. Cazorla, and D. Steenari, "GPU4S: Embedded GPUs in Space," in 22nd Euromicro Conference on Digital System Design, DSD 2019. Kallithea, Greece: Institute of Electrical and Electronics Engineers Inc., aug 2019, pp. 399–405.

[404] L. Kosmidis, I. Rodriguez, Á. Jover, S. Alcaide, J. Lachaize, J. Abella, O. Notebaert, F. J. Cazorla, and D. Steenari, "GPU4S: Embedded GPUs in space - Latest project updates," Microprocessors and Microsystems, vol. 77, p. 103143, sep 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0141933120303100

[405] H. Marques, K. Foerster, M. Bargholz, M. Tali, L. Mansilla, and D. Steenari, "Development methods and deployment of machine learning model inference for two Space Weather on-board analysis applications on several embedded systems," in ESA Workshop on Avionics, Data, Control and Software Systems (ADCSS). ESA, nov 2021, pp. 1–14.

[406] HiTech Global, "Xilinx ZYNQ UltraScale+ RFSoC FMC+ Board," p. 1, 2022. [Online]. Available: http://www.hitechglobal.com/Boards/RFSOC{_}FMC.htm

[407] Alpha Data, "ADM-VA600 User Manual," Edinburgh, Tech. Rep., nov 2023. [Online]. Available: https://www.alpha-data.com/xml/user{_}manuals/adm-va600usermanual{_}v1{_}0.pdf

[408] ——, "ADK-VA600 Datasheet," Edinburgh, Datasheet October, oct 2023. [Online]. Available: https://www.alpha-data.com/xml/product{_}datasheets/adk-va600{_}v1.7.pdf

[409] K. Ferrone, C. Willis, F. Guan, J. Ma, L. Peterson, and S. Kry, "A Review of Magnetic Shielding Technology for Space Radiation," Radiation 2023, Vol. 3, Pages 46-57, vol. 3, no. 1, pp. 46–57, mar 2023. [Online]. Available: https://www.mdpi.com/2673-592X/3/1/5/htmhttps://www.mdpi.com/2673-592X/3/1/5

[410] N. Ya'acob, A. Zainudin, R. Magdugal, and N. F. Naim, "Mitigation of space radiation effects on satellites at Low Earth Orbit (LEO)," Proceedings - 6th IEEE International Conference on Control System, Computing and Engineering, ICCSCE 2016, pp. 56–61, apr 2017.

[411] O. Gutiérrez, M. Prieto, A. Perales-Eceiza, A. Ravanbakhsh, M. Basile, and D. Guzmán, "Toward the Use of Electronic Commercial Off-the-Shelf Devices in Space: Assessment of the True Radiation Environment in Low Earth Orbit (LEO)," Electronics 2023, Vol. 12, Page 4058, vol. 12, no. 19, p. 4058, sep 2023. [Online]. Available: https://www.mdpi.com/2079-9292/12/19/4058/htmhttps://www.mdpi.com/2079-9292/12/19/4058

[412] Z. W. Han, K. F. Song, S. J. Liu, Q. F. Guo, G. X. Ding, L. P. He, C. W. Li, H. J. Zhang, Y. Liu, and B. Chen, "Lightweight Omnidirectional Radiation Protection for a Photon-Counting Imaging System in Space Applications," Applied Sciences 2023, Vol. 13, Page 5905, vol. 13, no. 10, p. 5905, may 2023. [Online]. Available: https://www.mdpi.com/2076-3417/13/10/5905/htmhttps://www.mdpi.com/2076-3417/13/10/5905

[413] Z. Vahedi, A. O. Ezzati, and H. Sabri, "Design of a space radiation shield for electronic components of LEO satellites regarding displacement damage," The European Physical Journal Plus 2024 139:2, vol. 139, no. 2, pp. 1–8, feb 2024. [Online]. Available: https://link.springer.com/article/10.1140/epjp/s13360-024-05025-1

[414] Radiation Handbook for Electronics, 2019, no. SGZY002A. [Online]. Available: www.ti.com/radbook

[415] C. I. Underwood and M. K. Oldfield, "Observed radiation-induced degradation of commercial-off-the-shelf (COTS) devices operating in low-Earth orbit," IEEE Transactions on Nuclear Science, vol. 45, no. 6, pp. 2737–2744, 1998.

[416] AMD XILINX Inc., "XQR Versal for Space 2.0 Applications," AMD XILINX Inc., San Jose, CA, Product Brief, 2022.

[417] J. Cornebise, I. Oršolić, and F. Kalaitzis, "Open high-resolution satellite imagery: The worldstrat dataset–with application to super-resolution," arXiv preprint arXiv:2207.06418, 2022.

[418] A. Van Etten, D. Lindenbaum, and T. M. Bacastow, "Spacenet: A remote sensing dataset and challenge series. arxiv 2018," arXiv preprint arXiv:1807.01232, 1807.

[419] M. Schmitt, S. A. Ahmadi, and R. Hänsch, "There is no data like more data-current status of machine learning datasets in remote sensing," in 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS. IEEE, 2021, pp. 1206–1209.

[420] S. Ayesha, M. K. Hanif, and R. Talib, "Overview and comparative study of dimensionality reduction techniques for high dimensional data," Information Fusion, vol. 59, pp. 44–58, 2020.

[421] J. Zhang, J. Yu, and D. Tao, "Local deep-feature alignment for unsupervised dimension reduction," IEEE Transactions on Image Processing, vol. 27, no. 5, pp. 2420–2432, 2018.

[422] G. T. Reddy, M. P. K. Reddy, K. Lakshmanna, R. Kaluri, D. S. Rajput, G. Srivastava, and T. Baker, "Analysis of dimensionality reduction techniques on Big Data," IEEE Access, vol. 8, pp. 54 776–54 788, 2020.

[423] R. M. Gahar, O. Arfaoui, M. S. Hidri, and N. B. Hadj-Alouane, "A distributed approach for high-dimensionality heterogeneous data reduction," IEEE Access, vol. 7, pp. 151 006–151 022, 2019.

[424] O. A. Abdullah, H. Al-Hraishawi, and S. Chatzinotas, "Deep learning-based device-free localization in wireless sensor networks," in IEEE Wireless Commun. Net. Conf. (WCNC), Mar. 2023, pp. 1–6.

[425] H. Lee, R. Grosse, R. Ranganath, and A. Y. Ng, "Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations," in Int. Conf. on machine learning, 2009, pp. 609–616.

[426] R. Abdulhammed, H. Musafer, A. Alessa, M. Faezipour, and A. Abuzneid, "Features dimensionality reduction approaches for machine learning based network intrusion detection," Electronics, vol. 8, no. 3, 2019.

[427] H. Shirmard, E. Farahbakhsh, A. Beiranvand Pour, A. M. Muslim, R. D. Müller, and R. Chandra, "Integration of selective dimensionality reduction techniques for mineral exploration using ASTER satellite data," Remote Sensing, vol. 12, no. 8, 2020.

[428] V. Monzon Baeza, F. Ortiz, S. Herrero Garcia, and E. Lagunas, "Enhanced communications on satellite-based iot systems to support maritime transportation services," Sensors, vol. 22, no. 17, 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/17/6450

[429] S. Cheng, Y. Gao, X. Li, Y. Du, Y. Du, and S. Hu, Blockchain Application in Space Information Network Security: Third International Conference, SINC 2018, Changchun, China, August 9–10, 2018, Revised Selected Papers, 01 2019, pp. 3–9.

[430] L. Pellaco, N. Singh, and J. Jaldén, "Spectrum prediction and interference detection for satellite communications," 10 2019.

[431] H. Xu, P. V. Klaine, O. Onireti, B. Cao, M. Imran, and L. Zhang, "Blockchain-enabled resource management and sharing for 6g communications," Digital Communications and Networks, vol. 6, no. 3, pp. 261–269, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352864820300249

[432] S. Laaper, "Using blockchain to drive supply chain transparency future trends in supply chain." [Online]. Available: https://www2.deloitte.com/us/en/pages/operations/articles/blockchain-supply-chain-innovation.html

[433] R. Xu, Y. Chen, E. Blasch, and G. Chen, "Exploration of blockchain-enabled decentralized capability-based access control strategy for space situation awareness," Opt. Eng, vol. 58, no. 4, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352864820300249

[434] H. Ibrahim, M. A. Shouman, N. A. El-Fishawy, and A. Ahmed, "Literature review of blockchain technology in space industry:

Challenges and applications," in 2021 International Conference on Electronic Engineering (ICEEM), 2021, pp. 1–8.

[435] L. Clark, Y.-C. Tung, M. Clark, and L. Zapanta, "A blockchain-based reputation system for small satellite relay networks," in 2020 IEEE Aerospace Conference, 2020, pp. 1–8.

[436] F. Tang, C. Wen, L. Luo, M. Zhao, and N. Kato, "Blockchain-based trusted traffic offloading in space-air-ground integrated networks (sagin): A federated reinforcement learning approach," IEEE Journal on Selected Areas in Communications, vol. 40, no. 12, pp. 3501–3516, 2022.

[437] S. Prakash, M. Stewart, C. Banbury, M. Mazumder, P. Warden, B. Plancher, and V. J. Reddi, "Is tinyml sustainable? assessing the environmental impacts of machine learning on microcontrollers," arXiv preprint arXiv:2301.11899, 2023.

[438] J. ur Rehman, H. Al-Hraishawi, and S. Chatzinotas, "Quantum approximate optimization algorithm for knapsack resource allocation problems in communication systems," in IEEE Int. Conf Commun. (ICC), Rome, Italy, Jun. 2023, pp. 1–6.

[439] L. Oleynik, J. ur Rehman, H. Al-Hraishawi, and S. Chatzinotas, "Variational estimation of optimal signal states for quantum channels," IEEE Trans. on Quantum Eng., vol. 5, pp. 1–8, 2024.

[440] H.-Y. Huang, M. Broughton, J. Cotler, S. Chen, J. Li, M. Mohseni, H. Neven, R. Babbush, R. Kueng, J. Preskill, and J. R. McClean, "Quantum advantage in learning from experiments," Science, vol. 376, no. 6598, pp. 1182–1186, Jun. 2022.

[441] M. C. Caro, H.-Y. Huang, M. Cerezo, K. Sharma, A. Sornborger, L. Cincio, and P. J. Coles, "Generalization in quantum machine learning from few training data," Nature Communications, vol. 13, no. 1, p. 4919, Aug. 2022.

[442] "Cloud Quantum Computing Service - Amazon Braket - AWS." [Online]. Available: https://aws.amazon.com/braket/

[443] "IBM Quantum Computing." [Online]. Available: https://ibm.com/quantum/

[444] "Quantum Computing for Developers | D-Wave." [Online]. Available: https://www.dwavesys.com/solutions-and-products/developer/

[445] H. Al-Hraishawi, J. ur Rehman, M. Razavi, and S. Chatzinotas, "Characterizing and utilizing the interplay between quantum technologies and non-terrestrial networks," IEEE Open J. Commun. Soc., vol. 5, pp. 1937–1957, Mar. 2024.

[446] A. Zappone, M. Di Renzo, and M. Debbah, "Wireless networks design in the era of deep learning: Model-based, ai-based, or both?" IEEE Transactions on Communications, vol. 67, no. 10, pp. 7331–7376, 2019.

[447] N. Shlezinger, J. Whang, Y. C. Eldar, and A. G. Dimakis, "Model-based deep learning," Proceedings of the IEEE, 2023.

[448] M. Kochupillai, M. Kahl, M. Schmitt, H. Taubenböck, and X. X. Zhu, "Earth observation and artificial intelligence: Understanding emerging ethical issues and opportunities," IEEE Geoscience and Remote Sensing Magazine, 2022.

[449] F. G. Ortíz-Gómez, R. Martínez-Rodríguez-Osorio, and S. Landeros-Ayala, "Method of optimizing the costs of a satellite network in ka and q/v bands in the feeder link," in 35th AIAA International Communications Satellite Systems Conference, 2017, p. 5442.