Centralized and Decentralized ML-Enabled Integrated Terrestrial and Non-Terrestrial Networks

Mehmet Ali Aygül*†, Halise Türkmen‡, Mehmet İzzet Sağlam§, Hakan Ali Çırpan*, Hüseyin Arslan‡

*Department of Electronics and Communications Engineering, Istanbul Technical University, Istanbul, 34467 Turkey
†Department of Research & Development, Vestel, Manisa, 45030 Turkey
‡Department of Electrical and Electronics Engineering, Istanbul Medipol University, Istanbul, 34810 Turkey
§Department of Research & Development, Turkcell, Istanbul, 34880 Turkey

E-mails: {aygul21, cirpanh}@itu.edu.tr, {hturkmen,huseyinarslan}@medipol.edu.tr, izzet.saglam@turkcell.com.tr

Abstract—**Non-terrestrial networks (NTNs) are a critical enabler of the persistent connectivity vision of sixth-generation networks, as they can service areas where terrestrial infrastructure falls short. However, the integration of these networks with the terrestrial network is laden with obstacles. The dynamic nature of NTN communication scenarios and numerous variables render conventional model-based solutions computationally costly and impractical for resource allocation and parameter optimization. Machine learning (ML)-based solutions can perform a pivotal role due to their inherent ability to uncover the hidden patterns in time-varying, multi-dimensional data with superior performance and less complexity. Centralized ML (CML) and decentralized ML (DML), named so based on the distribution of the data and computational load, are two classes of ML that are being studied as solutions for the various complications of terrestrial and non-terrestrial networks (TNTN) integration. Both have their benefits and drawbacks under different circumstances, and it is integral to choose the appropriate ML approach for each TNTN integration issue. To this end, this paper goes over the TNTN integration architectures as given in the 3GPP standard releases, proposing possible scenarios. Then, the capabilities and challenges of CML and DML are explored from the vantage point of these scenarios.**

Index Terms—**Centralized learning, decentralized learning, integrated terrestrial and non-terrestrial networks, machine learning, non-terrestrial networks.**

I. INTRODUCTION

The conclusion of fifth-generation (5G) standardization efforts and subsequent roll-outs have impelled academic and industry stakeholders to undertake the sixth-generation (6G) goal: persistent connectivity, or, satisfying the need for seamless, reliable, high throughput connectivity at all times and locations [1]. This is a challenging objective for areas with limited-to-none cellular infrastructure, scenarios where high speed vehicles are involved, and extremely dense areas. Non-terrestrial networks (NTNs), are an attractive enabler of the 6G vision due to their large coverage areas and limited reliance on terrestrial infrastructure [2]. As such, multiple entities have been tasked with determining the exigencies for effective terrestrial and NTNs (TNTNs) integration [3].

TNTN integration is a formidable task, with the typical difficulties of heterogeneity in networks further encumbered by challenges such as NTN device/network identification, continuous positioning and mobility tracking, cell/satellite re/selection and optimization, and beam management. The

difficulty in TNTN integration is three fold. Firstly, the information required for the optimization, such as satellite/user equipment (UE) position/mobility, channel tracking, is difficult to collect or obtain at the optimization device. Secondly, the optimization problems themselves are highly dimensional and complex, containing many variables such as UE position and mobility, cell size and mobility, non-terrestrial device trajectory, QoS requirements, and so on. Finally, mobility of NTNs and UE devices require frequent re-optimizations, once every 8-10 minutes at in the case of low earth orbit (LEO) satellites [4]. This renders model-based solutions impractical, as collecting the parameters for the optimization and performing the computation takes half this time, if not more [4].

Machine learning (ML) algorithms are well equipped for solving these multi-dimensional optimization problems via their inherent ability to detect complex patterns [2]. Nonetheless, these algorithms cannot be used blindly. Their performance varies based on factors such as computational complexity, amount of training data required, and the applicability of the trained model to general scenarios. Another factor is the preferred control and processing schemes: centralized or decentralized. Individual or central devices may not have the processing capability to manage the increasingly complicated computations or the data used for network optimization may not be procurable at one location. On the other hand, coordination in centralized control and processing is much easier.

With respect to these factors, and others discussed in this paper, ML approaches can fall under two main categories: centralized machine learning (CML) and decentralized machine learning (DML), so-called based on the host device(s) of the data and training process. However, choosing the appropriate approach for the TNTN scenarios is still an open issue [5], which this paper aims to shed light on. This paper:

- Goes over the use-cases and scenarios for integrated TNTN and the properties of the associated devices, classifying them into *connecting* and *connected devices*.
- Examines strengths and weaknesses of CML and DML, with respect to the 3rd generation partnership project (3GPP) NTN use-cases and possible TNTN scenarios.
- Suggests appropriate ML approaches for some TNTN scenarios and architectures with sound reasoning.

Compared to existing works in the literature, which focus on implementing various ML techniques on a single facet of NTN operations, such as enabling Internet of things (IoT) [6], handover optimization [7], integrating LEO satellites and multi-unmanned aerial vehicles (UAVs) [8], sustainable maritime networking [9], and coverage optimization [10], this paper aims to initiate dialog on the suitability of different ML approaches for various TNTN integration scenarios and issues.

II. NTNs IN 5G NR

NTN systems consist of non-terrestrial devices, encompassing satellites and high altitude platform station (HAPS). Their architectures include an aerial/space station that functions similarly to a terrestrial base station (BS) or repeater, a service link between the terrestrial terminals and the aerial/space station, and a gateway that connects the non-terrestrial access network to the core network via a feeder link. The payload of the non-terrestrial device can either be transparent/bent-pipe, where frequency filtering, conversion, and amplification operations can be applied, or regenerative, where demodulation/decoding, switch/routing, and coding/modulation can be applied as well.

A. NTN Devices and UEs

The devices in integrated TNTNs can be classified into six groups: satellites, HAPS, low altitude aerial vehicles (AVs), maritime vehicles, high speed terrestrial vehicles (HSTVs), and mobile UEs, as depicted in Fig. 1. Some information regarding the operating and channel conditions and connectivity concerns are given in Table I, and additional information is given below. Here, *connecting devices* are the non-terrestrial platforms and *connected devices* are devices which are able to achieve ubiquitous connectivity through NTNs or the connecting devices. The common issue for all connected devices and scenarios is the lack of or limited terrestrial architecture.

- *Satellite*: Satellites are classified as geostationary earth orbits (GEO), medium earth orbit (MEO), and LEO. GEOs are considered stationary, while MEOs and LEOs have a fixed orbit. LEO satellite constellations, such as OneWeb and Starlink, intend to provide global connectivity.
- *HAPS*: At a lower altitude than satellites, HAPS have limited, primary terrestrial network (TN) connections, and wide, secondary satellite connections. 3GPP has designated them as international mobile BSs.
- *Low altitude AVs*: Limited connectivity was provided for communication with control centers in the past, but this is insufficient for the IoT era.
- *Maritime vehicles*: Maritime operations require open-sea and land-sea communication. [9], [11] consider maritime communication services as a use-case of TNTNs in 5G new radio (NR) networks.
- *HSTVs*: These vehicles, such as high speed trains, are becoming more autonomous with the help of IoT devices. Additionally, on-board customers have become accustomed to continuous connectivity and expect a certain level of communication services. This requires massive number of secure and sometimes broadband connections.
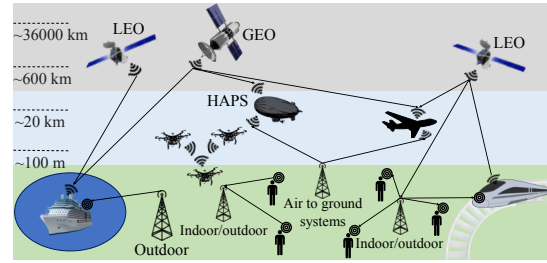

Fig. 1. Use-cases of the integrated TNTNs.

- *Mobile UE*: The mobile UEs can be pedestrians and UEs in automobiles. Connectivity is possible in urban environments due to the presence of TN infrastructure. However, this infrastructure may be overloaded in times or locations of extreme UE density. Rural or uninhabited locations also necessitate alternative solutions.

B. Use-Cases

While the devices and their operation scenarios effectively give insight to the challenges, the use-cases effectively determine the requirements pertaining to communication. The type of service these users require is explained herein [12].

- *Connectivity*: TNs alone are incapable of providing global, ubiquitous connectivity in the following scenarios:
  1) *Rural/uninhabited locations*: These locations have little to none permanent residents or visitors. As such, installing infrastructure is not feasible for operators.
  2) *Extremely dense populations/crowded events*: Concerts, sports matches, and other events push the limits of cellular networks and significantly degrade the quality of service.
  3) *High mobility UEs*: These UEs are subject to constant handovers, lowering the quality of service for the UEs and adding a burden to the networks.

These scenarios can exist in the same instance, i.e.: high speed passenger trains or commercial airplanes both contain a large amount of UEs and pass through locations with no or limited cellular infrastructure. Conditioned on the service, connectivity can be multi, fixed, mobile, or mobile-hybrid. The categories proposed to enable connectivity are [12]:

- *Multi/resilient*: In multi-connectivity, a UE has multiple connections to increase data rate or as a back-up connection for reliability. Here, the NTN connection can be the back-up or main connection. Resilient connectivity aims to prevent complete network outage. Thus, the NTN is expected to provide broadband connectivity between the UEs and the core network in outage scenarios.
- *Fixed/trunking*: In fixed connectivity, NTNs will provide the only connection. Planned to be deployed in rural or ad-hoc areas, broadband connectivity between the core network and nomadic UEs is aimed. Trunking is to provide temporary 5G connectivity in emergency situations.
- *Mobile cell*: This is the solution for the third scenario where connectivity is compromised. Here, the NTN is expected to provide broadband connectivity between the core network and UEs on board a highly mobile platform.

TABLE I
DEVICE CATEGORIES IN NTNs USE-CASES.

Device Category	Altitude	Mobility	Channel	Connectivity Concerns
Connecting Devices				
Satellite	GEO: 35786 km MEO: 7000-20000 km LEO: 600-1200 km	GEO: None MEO: High, circular orbit LEO: High, circular orbit	Free space with atmospheric & scintillation losses - Sat2Sat: LoS - Sat2(dense)Urban UE: nLoS - Sat2Rural UE: LoS	- Large delay & Doppler spread - Strong fading effects - Satellite mobility - nLoS connections
HAPS	8-50 km	Low	Free space with AWGN, 2-tap model - HAPS2HAPS/Sat: LoS - HAPS2UE: LoS/nLoS	- UE positioning - Trajectory planning
Connected Devices				
Low altitude AVs	0.1-6 km	High, known trajectory	Free space - AV2AV: LoS - AV2HAPS/Sat: LoS - AV2UE: nLoS	- Frequent handovers - Doppler shifts - Dynamic channel conditions - May cross national borders
Maritime vehicles	Sea level	Low	Free space with ocean clutter and evaporation duct	- Large distances between UEs - Unique channel conditions
HSTVs	Terrestrial	High	Varies depending on environment - (Dense) Urban: nLoS - Suburban/Rural: LoS	- Doppler spread - Frequent handovers - May cross national borders
Mobile UEs	Terrestrial	Low	Indoor: nLoS Outdoor: nLoS/LoS	- UE positioning - Undeterministic UE trajectory - Limited device capabilities

– *Mobile-hybrid*: This is for enabling connectivity to UEs on public transport with fixed routes. NTNs will provide a back-up or auxiliary connection for routes where the TNs have a limited capacity.

– *Hot-spot-on-demand*: Here, NTNs are expected to provide temporary 5G connectivity to under-served areas.

• *Broadcasting*: This encompasses direct-to-node, direct-to-mobile, and edge network delivery broadcasts. In the former, the information is transmitted to an access point, from which it is distributed to the UEs within the network. Direct-to-mobile broadcast is used to transmit information to multiple UEs simultaneously. Such a service is required for issuing alerts to the community or responders during emergency situations and global software updates. Edge-network delivery is used to offload popular content or system updates to the edge nodes for caching and redistribution. Here, broadband connectivity is expected of the NTN devices.

• *Public safety*: The aim here is to provide connectivity between the emergency responders, regardless of their location and presence of terrestrial infrastructure. This can be divided into wide-area, local, and regional public safety. The role of the NTNs is to provide connectivity between the emergency responder UEs, tactical cells, and the core network.

• *IoT service*: Depending on the mobility and coverage area, these use-cases can be divided into wide-area and local IoT service connectivity. IoT devices on HSTVs and other scenarios involving mobility over a known area are expected to be supported by NTNs providing wide-area connectivity. Others, like devices on smart grid, are expected to be supported by NTNs providing local area connectivity. Here, the NTN will provide connectivity between the IoT devices, their hub/central point, and the core network.

C. Existing Integration Issues and 3GPP Studies

Integrated TNTNs require a flexible centralized or decentralized architecture that can manage traffic smoothly between TNs and NTNs for better, more intelligent utilization of the network resources. At the minimum, idle and active UEs should be able to get ubiquitous coverage worldwide without receiving a congestion rejection or service degradation.

Achieving these goals has several challenges. NTNs have a considerably larger propagation delay than TNs, increasing service interruption time during idle mode service continuity or active mode handover. Another challenge is the number of handovers in active mode due to non-GEO satellite movements. Meaning, while the coverage area of a GEO satellite is static with fixed large spot cells, LEO coverage area is changed with time and the satellite's ephemeris, requiring frequent updates or handovers. Additionally, the cells of the NTNs have a significant signal difference between the cell center and edge. As such, the same or similar transmission parameters cannot be used for UEs at both locations. The time delay brought on by the random access procedure is another challenge, because this procedure affects UE connection establishment and time synchronization, while integrated TNTN needs to support high-speed UE handover and service continuity, requiring a minimum response time in the random access procedure.

In this regard, NTNs have been a focus of the 5G standardization efforts by 3GPP, with related works in Release (Rel)-15, Rel-16, and Rel-17. Rel-15, started in 2017, reported the results of a feasibility study targeting the channel models and deployment scenarios [12]. Subsequently, Rel-16 defined the minimum changes to the present standards to integrate the essential NTN features [13], while Rel-17, completed in 2022, focused on the transparent payload architecture with earth-fixed tracking areas and frequency division duplex systems [14]. A study phase for network-verified NTN UE location was completed, and its normative phase is approved in 3GPP Plenary #98e electronic meeting [15].

The 3GPP Rel-18, Rel-19, and Rel-20 are the upcoming releases for 5G-Advanced and focus on fine-tuning the scenarios and the usage of NTNs. Currently, the 3GPP are working on Rel-18, the NTN IoT enhancement [16]. This release aims to cover the integration of TNs and NTNs, throughput performance, and the optimization of the global navigation satellite system sparse usage to decrease power consumption for long-term connections. Additionally, enhanced machine

type communication with minimum feature updates using TNTNs is also within the scope of this release. The Rel-18 study items also include the integrated TNTNs mobility, service continuity, and coverage enhancement. These discussions cover the potential low rate codecs performance enhancements in a link budget limited context, including voice over NR.

III. CML AND DML FOR INTEGRATED TNTNs

Pervasive system intelligence is critical for the evolution and long-term operation of integrated TNTNs. Particularly, real-time decision-making substantially enhances network performance. The ML-based remote control allows for further investigation of fundamental and unexplored characteristics of TNTN and the creation of novel communications and networking technologies, such as new protocol designs, architectures, and advanced algorithms. Network designs can be optimized to increase spectrum access flexibility, while radio channels can be modeled efficiently. Furthermore, using ML in TNTN enables seamless autonomous communication in the presence of channel effects, such as attenuation, fading, and interference, and TNTN integration can be done without the need for prior mathematical study and modeling. However, ML algorithms can not be used blindly; rather, how and where to use them should be investigated to get the maximum benefit from the ML algorithms.

CML infrastructures are designed to meet the requirements of numerous ML models that demand locality and persistent training. The data is collected in a powerful and robust device, which runs the ML algorithm. It comes with the advantages of fewer resources required on training departments, networking opportunities, reduced buddy costs of training materials, and best practices across multiple sites. Still, CML-based systems face challenges such as data delivery costs (latency), the possibility of involving poor channel and unstable connectivity conditions, coordination and scheduling durations, and generic training results, rendering them unsuitable for real-time applications. Additionally, CML systems require sharing of sensitive operational data, which is a privacy issue. Also, there are different use-cases, devices, and user types, with various problems, scenarios, and requirements. Thus, CML requires coordination between different use-cases and problems.

DML allows a set of local devices to locally and collaboratively participate in the training process of a global model without having to upload their local raw data to centralized servers. Thus, they restrict the amount of data transmission across the network. This adds a privacy feature and removes the delivery time, which is the time takes for data to be prepared and delivered to a central device. However, some devices may not have the capability to process complex mathematical equations of ML, e.g., IoT and reduced capability devices. Additionally, DML only trains with its own dataset, which may restrict the learning capability and produces internal models, i.e.: models which cannot be utilized in general scenarios.

Recently, implementation of federated learning (FL), a specialized DML approach, has gained interest [17]. Here, clients do local training and send their model parameters to
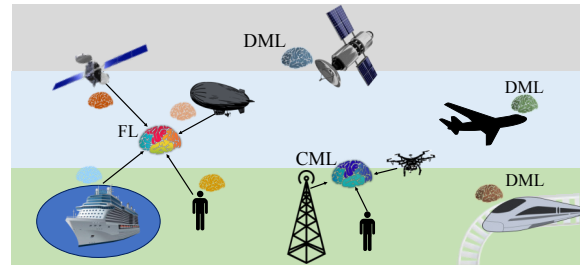

Fig. 2. Example scenarios for CML, DML, and FL for integrated TNTN.

an aggregator for further inference. This can simultaneously address the privacy issues brought by CML techniques and the lack of generality of the models trained by DML techniques. An illustration depicting the possible CML, DML, and FL approaches are given in Fig. 2. In this figure, a LEO satellite, maritime UE, HAPS device, and a mobile UE train their models locally (coarse learning) and share the trained parameters with the FL cloud for fine learning. For CML approach, the BS, mobile UE, and drone may send their data to a central device, where the model is trained using all the datasets and a generic model is obtained. For the DML approach, a train, plane, and GEO satellite can learn their individual model parameters, using the data specifically available for them.

Specific scenarios and design criteria where CML and/or DML approaches are useful are given below. Note that while one approach can be beneficial for a scenario, another approach may also be beneficial from a different perspective. Accordingly, hybrid approaches can be useful for a scenario.

- *Updating the location of the satellites*: When the locations of several LEO satellites need to be updated frequently, CML could cause problems due to delivery time and synchronization between different devices. Also, there can be bottlenecks and single-point failure problems for mobile LEO satellites. Therefore, a DML approach can be promising for this problem.
- *Propagation channel and synchronization*: There are different delay and Doppler models. For example, satellite communications have outdoor and line of sight (LoS) conditions, whereas indoor and non-LoS (nLoS) communication conditions are addressable using HAPS. The signal is primarily direct LoS for satellite-based systems and follows a Ricean distribution with a robust direct signal component; slow fading is possible due to transient signal masking, such as beneath trees and bridges. The signal in HAPS-based systems also follows a Ricean model, however, it comprises of considerable multipath components. Therefore, the receiver synchronization configuration, such as the preamble sequence and aggregation to take into account the Doppler and specific multipath channel models and cyclic prefix to compensate the delay spread, at both UE and Next Generation NodeB (5G gNB) levels are different. Thus, the same ML algorithm may not work, so, a CML device should be capable of doing feature extraction for all of the problems, which may be

difficult in several use-cases. However, if DML is used, each device can extract the features by itself and run its own algorithms. Therefore, the DML approach could perform better in this scenario.

- *Cell pattern generation*: Compared to cellular networks, satellite and HAPS systems often have larger, possibly mobile, cells. These cells can produce a high differential propagation delay between a UE at the cell center and a UE at the cell edge, particularly at low operational elevation angles. This affects contention-based access channels when the network does not know where the UEs are. Here, the differential latency caused by the large cell size may cause a near-far effect during the initial access procedure. To boost performance, an extended acquisition window may be required. However, if the UE position is known during a session, the network can correct for the differential latency. As a result, specialized signaling may be required to support these larger, mobile cells for broadcast services. Since specialized signaling is required, a DML approach is more promising.

- *Service continuity between TN and NTN*: To ensure service continuity, a handover to or from the satellite/HAPS system can occur whenever a UE leaves or enters the cellular coverage. The handover triggering mechanisms may differ depending on the circumstances, such as terminating the satellite connection as soon as there is an adequate-strength cellular signal, but only terminating the cellular connection when there is very little signal strength. The service enablers, characteristics, and measurement reports of both access technologies should be considered during the handover operation. Since there are several aspects that should be investigated jointly, CML-based approach is promising for this issue. On the other hand, the differences in the propagation delay between NTNs and cellular networks will cause substantial jitter. If the service continuity is ensured with CML, an extra delay time of delivery time and scheduling will be added to the system as explained before. Therefore, if the delay is important for the use-case, DML can be preferred. Alternatively, to use the advantages of both CML and DML, FL can be used for this scenario.

- *Satellite and HAPS-based design*: Several design criteria exist for satellite and HAPS-based communication systems. Some of these are:
  - Maximizing throughput from the uplink UE and the downlink satellite/HAPS for a given transmit power.
  - Maximizing service availability in cases of deep fading.
  - Maximizing the throughput/power ratio; the operation point in the power amplifier at the satellite or the UE should be adjusted as close to the saturation point as possible when needed.
  - Maximizing signal availability with slow and deep fading; vital for UE near the cell edge, modulation and coding techniques with very low SNR operating points or other options should be studied.

  - The MAC layer should be able to flexibly and dynamically allocate physical resource blocks to maximize spectrum efficiency and accommodate low-power terminals.

Since there are multiple different design criteria and they should be taken into consideration jointly, a CML approach can yield a better performance.

- *Terminal mobility*: Enabling communication for very high speed UEs, e.g. aircraft systems up to 1000 km/h speed [18], is a challenging task. In these speeds, CML approaches will not work, as sharing data with other nodes will cause latency. Thus, DML is more promising.

- *Security*: Integrated TNTNs can manage sensitive information, such as user mobility, service usage statistics or operator data. Sharing this data may not be preferred by operators or even legal, depending on the nation's laws. Here, DML can be the only option available.

- *Dynamic service deployment*: The presence of numerous NTNs, and varying ground-UE demands, could have an effect on dynamic service deployment policies. Learning their data together may increase the performance of the system. CML can be useful in these networks.

- *Energy efficiency*: CML can be designed as a service which supports mobile network operators for energy efficiency, operational efficiency, and delivering ubiquitous coverage in machine type communications. This service can help mobility and service continuity for TNTN machine type communication with easy-to-deploy, always available, secure, and reliable communications. IoT, reduced capability devices, or sensors do not need to have complex compute resources with a CML approach.

- *Radio resource management adapted to network topology*: The particular cell patterns of NTNs need to be accommodated via mobility management. Also, cells in the NTN may pass national borders. This will have an effect on cell identification, tracking and location area design, roaming and charging procedures, and location-based services. Thus, NTN should be aware of several procedures simultaneously. This can be possible with a CML approach. Also, the access control mechanism must respond quickly to meet fluctuating traffic demand while also taking UE mobility requirements into account. Thus, both of them are learned jointly with a CML approach.

- *Frequency planning and channel bandwidth*: There are several aspects here in integrated TNTN. For example, frequency reuse and flexibility of spectrum allocation in different cells may be supported. Also, there are techniques to minimize the risk of inter-cell interference for efficient spectrum usage. To enable the targeted spectrum and the pairing between uplink/downlink bands with precise band separation, the carrier numbering can be examined. Carrier aggregation can be employed to provide equal throughput while allowing for greater flexibility in carrier allocation between cells and conforming to frequency reuse limits. These aspects require the system

to learn the relationship between different parameters and adapt the upper layers, such as MAC and network layer signaling in a specific manner. Since CML is promising for jointly learning relationships between different problems, it may also be convenient here.

IV. CHALLENGES AND FUTURE DIRECTIONS

There are considerable challenges that need to be overcome in order to implement CML and DML approaches efficiently:

- *Simulation models*: Both CML and DML are data hungry. Since the implementation of integrated TNTNs are limited, it is difficult to get a real dataset. Therefore, simulation models for integrated TNTNs should be defined.
- *Simulation analysis*: Simulation analysis should be made for CML and DML. Possible scenarios are routing techniques with UAVs, satellites, and HAPS in hierarchical architecture, identification, localization and optimal trajectory design, analyses to ensure privacy, integrity, and secrecy, resource management, network planning, power control, received signal strength prediction, interference management, and transmission parameter tuning.
- *Number of updates*: This should be well optimized, along with the update message itself, i.e., the training derivatives, to reduce traffic.
- *Data*: A TNTNs system regularly generates data that is statistically unique from each other due to varied operation, or surroundings, i.e. in a non-independent identically distributed (i.i.d.) manner. Because both CML and DML relies on the i.i.d. assumption, unique strategies to handle statistical heterogeneity must be created.
- *Privacy*: It is necessary to take precautions to ensure that sensitive data is not relegated to specific individuals or devices. Deviating units are the most likely to be harmed since their usage patterns stand out and may influence the model in a unique way.
- *Dynamism*: The storage, computing, and communication capabilities of a TNTN system are heterogeneous. As a result, a TNTN training system must be dynamic or adapt to the device's lowest denominator.
- *Theoretical analysis*: Data driven vs. model-based algorithms' performance for TNTNs should be investigated.
- *Complexity*: Despite the advantages of CML and DML approaches, most ML approaches are computationally heavy. Therefore, these approaches should be investigated in terms of computational complexity, latency, and delay.
- *Selection of CML device*: This can be based on the device's processing capability, location, scheduling, and memory, all of which are critical for the performance of the chosen approach, and should be investigated further.

V. CONCLUSIONS

Integrating NTN devices and networks with the current TN technology brings about significant challenges. Much of these challenges are not present in TNs, and so require in-depth studies and novel solutions. Therefore, making 5G and beyond from space a reality also necessitates initiatives that go beyond standardization. This paper highlighted the importance of choosing the appropriate ML approach for several challenges of the integrated TNTN. The feasibility of using these ML approaches for each scenario was also debated. Because studies on CML and DML for TNTN integration are still recent, this paper also highlighted future research directions.

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