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## 6G-INTEGRATION-3

# Innovations for the NTN integration with 3GPP networks

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### Abstract

Currently (in the year 2022), about 2,500 satellites orbit the Earth. It is expected that this number will reach 50,000 satellites (i.e., a 20-fold increase) in the next 10 years, thanks to recent advances in low-cost satellite launches with high success rates. This document reviews the fundamentals of satellite communications and the latest advances in fault-tolerant onboard equipment, AI/ML-based applications in STIN, and advancements and deployments in Non-Terrestrial Networks (NTNs). Additionally, the document delves into the 3GPP Release 17 standard in the context of NTN and analyzes the state of the art in hardware fault tolerance strategies in the space segment, as well as the applications of AI/ML in optimizing the operation and performance of satellite communications

and High-Altitude Pseudo-Satellites (HAPS). Finally, the document concludes with a brief summary of the contributions and the analyzed state of the art.

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## Resumen Ejecutivo

En la actualidad (año 2022), unos 2.500 satélites orbitan la Tierra. Se espera que este número alcance los 50.000 satélites (es decir, un crecimiento 20 veces mayor) en los próximos 10 años, gracias a los recientes avances en materia de lanzamiento de satélites a bajo coste y con altas probabilidades de éxito. En este sentido, se espera que en los próximos años el mundo sea testigo de un aumento masivo de la conectividad móvil gracias a la combinación de despliegues 5G y satélites, construyendo la denominada Red Integrada Espacio-Terrestre (STIN), gracias a la aparición de las Redes No Terrestres (NTNs).

Este documento repasa los fundamentos de las comunicaciones por satélite y los últimos avances en relación con los equipos de a bordo tolerantes a fallos, las aplicaciones basadas en IA/ML en las STIN y los avances y despliegues en las NTN. Además, el documento profundiza en el estándar 3GPP Release 17 en el contexto de las NTN para después analizar el estado del arte en cuanto las estrategias para la tolerancia ante fallos en hardware en el segmento espacio, así como las aplicaciones de AI/ML en la optimización del funcionamiento y rendimiento de las comunicaciones por satélite y los HAPS. Finalmente, el documento concluye con un breve resumen sobre las contribuciones y el estado del arte analizado.

## Executive Summary

Currently (in the year 2022), about 2,500 satellites orbit the Earth. It is expected that this number will reach 50,000 satellites (i.e., a 20-fold increase) in the next 10 years, thanks to recent advances in low-cost satellite launches with high success rates. In this regard, the world is expected to witness a massive increase in mobile connectivity in the coming years, combining 5G deployments with satellites, forming what is called the Integrated Space-Terrestrial Network (STIN) through the emergence of Non-Terrestrial Networks (NTNs).

This document reviews the fundamentals of satellite communications and the latest advances in fault-tolerant onboard equipment, AI/ML-based applications in STIN, and advancements and deployments in NTN. Additionally, the document delves into the 3GPP Release 17 standard in the context of NTN and analyzes the state of the art in hardware fault tolerance strategies in the space segment, as well as the applications of AI/ML in optimizing the operation and performance of satellite communications and High-Altitude Pseudo-Satellites (HAPS). Finally, the document concludes with a brief summary of the contributions and the analyzed state of the art.

## 1. Introduction

The concept of using satellites for communications dates back to the late 20th century, but it wasn't until the Cold War that significant progress was made in developing the technology. In 1957, the Soviet Union launched the first artificial satellite, Sputnik 1, which prompted the United States to establish the Advanced Research Projects Agency Network (ARPANET) in 1969, which was the predecessor to the modern internet. Since then, the use of satellites for communications has continued to evolve and expand, and they are now used for a wide variety of applications, including television and radio broadcasting, telephone and internet service, GPS navigation, and more.

There are several different types of satellites that serve different purposes, including:

- Communication satellites: These satellites are used to transmit and receive communications signals, such as telephone and internet data, television and radio broadcasts, and GPS signals.
- Earth observation satellites: These satellites are used to observe and gather data about the Earth and its environment. This can include weather forecasting, mapping and surveying, and monitoring natural resources.
- Navigation satellites: These satellites are used to provide navigation and positioning information. The most well-known example is the Global Positioning System (GPS), which is operated by the US military and is available for civilian use.
- Science and research satellites: These satellites are used for scientific research, such as studying the Earth's climate and weather patterns, the solar system and beyond, and the effects of space on human physiology and biology
- Spy satellites: These satellites are used for surveillance and intelligence gathering. They can be equipped with a variety of sensors to collect information such as photographs and signals intelligence.
- Weather satellites: These satellites are used to observe and gather data about the Earth's atmosphere and weather patterns. This information is used for weather forecasting and monitoring severe weather events such as hurricanes and storms.
- Reconnaissance satellites: These are similar to Spy satellites, but they are focused on gathering information from specific area, often from countries that are not allies.
- Tactical military satellites: These satellites are intended for military operations, for command and control, communication relay, and navigation.
- CubeSats: These are a class of miniaturized, standardized and low-cost satellite for space research and space education.

In the USA, about 20% of the population lives in rural areas, which account for about 97% of the total land. This number grows to 28% in Europe, and about 40% world-wide. In many cases, fiber deployment does not reach rural areas (at least the last mile), since this results very expensive for network operators, hard to justify in terms of Average Revenue per User (ARPU). Indeed, it is estimated that every single meter of fiber connectivity costs approximately 100 US dollars. The largest share of this cost includes digging, trenching and the civil works in general [19].

In the past, long-range PONs were explored by the Google Fiber project, and wireless solutions like WiMAX, mmWave solutions or Google Loon were explored to reach difficult coverage areas. However, it seems that none of these solutions have been massively deployed. As a matter of fact, the Google Loon project was discontinued in 2021.

However, in the past years, the research community has witnessed a race toward deploying different satellite constellations to provide connectivity to rural areas. This is mainly due to the cost reduction in launching the satellites themselves, approximately 6,000 USD per kg of mass [15] for SpaceX Falcon 9. In this sense, it is estimated that approximately 2,500 satellites are currently orbiting the Earth, a number that is estimated to grow to 50,000 within 10 years [4].

Essentially, while GEO and MEO constellations suffer from high round-trip times (RTT), in the order of several hundreds of milliseconds, with subsequent performance degradation of TCP protocols, LEO constellations can reach few tens of milliseconds. Furthermore, High-Altitude Platforms (HAPs) operating at 20 Km distance can even reduce RTTs to few milliseconds.

It is worth noticing that light travels at approximately 300,000 km/s through the air, while it does at 200,000 km/s over silica fiber, that is, the air is 50% faster than silica fibers in terms of propagation delay. This translates into a propagation delay of 3.33  $\mu$ s/km for free-space communications and 5  $\mu$ s/km for fiber transmission. In fact, some authors claim that satellite communications can be faster than fiber in wide area scenarios above 1,000 km [9, 10], especially in those countries with difficult conditions for fiber deployment (i.e. desert, mountains, etc).

In particular, a number of companies have focused on deploying Low Earth Orbit (LEO) satellite constellations (between 500 - 1200 km altitude) since latency in these cases are moderate (few tens of milliseconds). In addition to providing coverage to rural areas, satellites can provide connectivity worldwide and are very resilient to natural disasters and wars. LEO satellite constellations can provide sufficient connectivity performance for Machine-Type Communications (MTC) and Mobile Broadband (MBB) in areas where fiber connectivity is difficult to provide [11], paving the way for Non-Terrestrial Networks (NTN) to complement existing Terrestrial Networks, both fixed and mobile. The authors of [7, 8] provide a summary of architectures and challenges to integrate LEO constellations in the 5G eco-system and even 6G [1]. A detailed survey on this matter is exhaustively studied in [20]. Our major companies are already deploying LEO satellite constellations, namely Telesat, Tesla's Starlink, OneWeb and Amazon. The authors in [5] provide a thorough comparison of the LEO constellations and features provided by these four major players, showing tens of milliseconds latency, average throughput of few Gb/s per satellite.

This article provides a technical review of recent progress and technology on satellite communications for providing connectivity in deep rural and remote areas. Vertical applications like rural broadband, IoT applications like smart agriculture and animal tracking, environmental protection and public safety, etcetera can represent interesting market opportunities to trigger satellite developments.



To accomplish this overview, Section 2 briefly reviews the most important design aspects of Satellite Communications. Section 3 introduces current mega-constellations and existing projects for NTN as of 2022. Section 4 reviews technologies for fault-tolerant switching tables. Section 5 provides an overview of AI/ML algorithms for satellite communications. Finally, Section 6 concludes this work with its main contributions.

## 2. An overview of satellite communications

### 2.1. Orbits and propagation delay

In general Non-Terrestrial Networks (NTNs) refer to networks providing connectivity through space-borne vehicles or airborne platforms, including satellites, etc. These provide radio connectivity between the User Equipment (UE) on the ground and the vehicle which, in addition, provide connectivity to Terrestrial Networks (TN) through Ground Based Gateways (see Fig. 1).

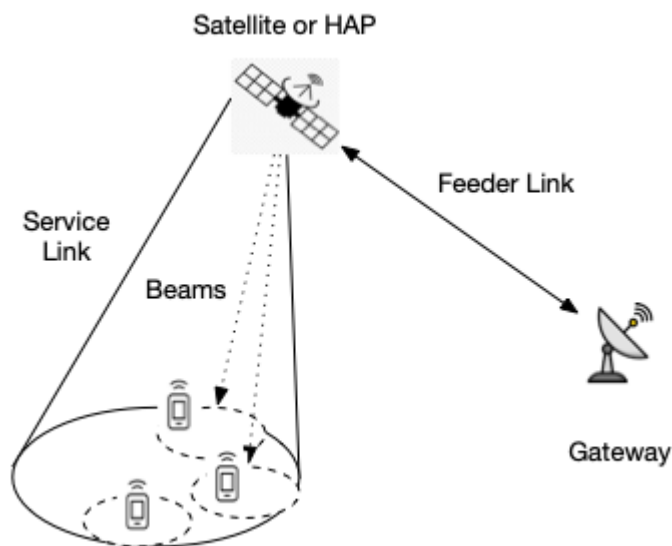


Fig. 1. Architecture and terminology.

Depending on the altitude of the space-borne, multiple NTN options are possible:

- Stationary satellites placed in GEO, operating at 35,876 Km altitude. GEO scenarios are often equipped with Very High Throughput Satellites (VHTS), providing tens or hundreds of Gb/s capacity each. In this case, Doppler effects are negligible, but propagation delays can reach up to several hundreds of milliseconds for transparent satellites.
- Non-stationary satellites positioned in MEO (7,000-25,000 Km) or LEO (300-2,000 Km), in relative motion to the earth. In these cases, latency values can be moderate, in the range of tens of milliseconds, but Doppler needs compensation. Satellite coverage and their cells may

be stationary or not. The former requires the beams fixed on Earth, while the latter simply implies that the beams move at the same speed of the satellites (typically few Km/s for LEO sats). In the case of non-stationary cells, methods for handover operations and roaming are required.

- High Altitude Platforms (HAPs) like planes or balloons, operating like satellites but closer to the Earth, at about 20 Km distance. HAPs latency values are often below 10 ms.

In this regard, it is worth remarking that latency heavily affects TCP throughput in TCP/IP based networks, as noted by the Mathis formula [16], further validated in [18]:

$$(1) \quad Throughput < \frac{MSS}{RTT} \frac{C}{\sqrt{p_{loss}}}$$

where MSS is the Maximum Segment Size and RTT is the end-to-end Round-Trip Time; C is a constant that can be estimated from measurements (a number between 1 and 1.5 typically) and  $p_{loss}$  is the packet loss probability, due to any factor (packet corruption, collisions in shared media or buffer overflow due to congestion).

**Numerical example:** As an example, consider a connection between two cities separated 200 ms, MSS of 1500 Bytes and packet loss probability of  $10^{-9}$  (typical fiber loss) [21]. Substituting in eq. 1, the maximum rate is 1.9 Gb/s (assuming  $C = 1$ ). If latency is doubled (i.e. 400 ms), then the maximum TCP throughput drops to 950 Mb/s. On the other hand, if the case of an unreliable link with packet loss probability is  $10^{-6}$ , then the throughput drops to 30 Mb/s for RTT values of 400 ms. Thus, TCP throughput benefits from both reliable and low-latency links.

## 2.2. Frequency bands

Both Fig. 2 and Table 1 summarise detailed information regarding frequency bands allocated by the ITU for satellite communications. Essentially, the L and S bands do not offer much bandwidth (tens/hundreds of KHz to few MHz typically) and are often destined to IoT applications.

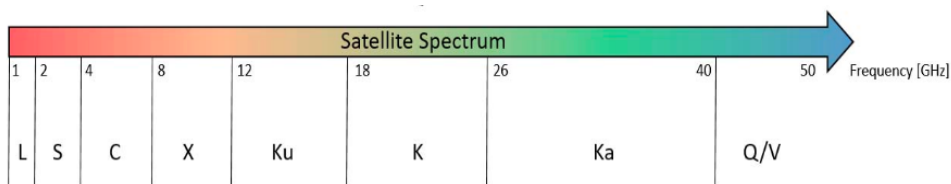


Fig. 2 Satellite spectrum [13].

The Ka and Ku bands provide more bandwidth (tens/hundreds MHz) and can be used to provide MBB connectivity, especially in cases with high antenna gains. Finally, the Q/V bands offer large bandwidth capacity values (hundreds MHz to few GHz) but are more subject to atmospheric losses and absorption from rain. In this regard, the V band can be used for inter-satellite links (ISL) since they are above the clouds, offering mesh connectivity between satellites. Also, some experimental scenarios consider the W Band (between 75-110 GHz) which provides even more bandwidth than Q and V bands, and should be also used for inter-satellite links (ISL) since this band heavily suffers from propagation impairments and rain fade.

Satellite band	Downlink (DL)	Uplink (UL)
L Band (GEO)	1518 – 1559 MHz	1626.5 – 1660.5 MHz 1668 – 1675 MHz
L Band (Non-GEO)	1613.8 – 1626.5 MHz	1610.0 – 1626.5 MHz
C Band	3400 - 4200 MHz 4500 - 4800 MHz	5725 - 7025 MHz
S Band	2160 -2200 MHz 2483.5 - 2500 MHz	1980 - 2025 MHz
Ku Band	10.7 - 12.75 GHz 13.75 - 14.5 GHz	12.75 - 13.25 GHz
Ka Band (GEO)	17.3 – 20.2 GHz	27.0 – 30.0 GHz
Ka Band (Non-GEO)	17.7 – 20.2 GHz	27.0 – 29.1 GHz 29.5 – 30.0 GHz
Q/V Band	37.5 – 42.5 GHz 47.5 – 47.9 GHz 48.2 – 48.54 GHz 49.44 – 50.2 GHz	42.5 – 43.5 GHz 47.2 – 50.2 GHz 50.4 – 51.4 GHz

Table 1. ITU-T Frequency allocations for satellite communications.

### 2.3. Link budget calculations

Classical link budget calculations for satellite communications follow the well-known Friis propagation model, where the power at the receiver antenna  $P_r$  (also referred to as signal strength  $S$ ) is:

$$(2) \quad P_r = P_t \frac{G_t G_r \lambda^2}{(4\pi)^2 d^2} = S$$

where  $P_t$  is the transmission power of the transmitting antenna,  $G_t$  and  $G_r$  are the transmission and reception gain of the two antennas, and  $\lambda$  and  $d$  are the transmission wavelength and slant range between the transmitter and receiver in the satellite link. Often, the product  $P_t G_t$  is called the EIRP or Effective Isotropic Radiated Power.

The receiving antenna both collects the above signal power  $S$  and noise  $N$ . The amount of noise collected follows:

$$(3) \quad N = k_B T B_w$$

where  $k_B$  is the Boltzmann constant ( $1.380649 \times 10^{-23} \text{ m}^2 \cdot \text{kg} \cdot \text{s}^{-2} \cdot \text{K}^{-1}$  or  $-228.6 \text{ dBW/KHz}$ ),  $T$  is the noise temperature and  $B_w$  is the bandwidth of the receiving filter. It is worth remarking that the noise temperature  $T$  can be computed from the noise figure (NF) as:

$$(4) \quad T = T_{ref} \left( 10^{\frac{NF}{10}} - 1 \right)$$

where the reference (ambient) temperature  $T_{ref}$  is often assumed  $290 \text{ K}$  (i.e.  $16.85 \text{ }^\circ\text{C}$ ). With these values of signal strength  $S$  and noise power  $N$  at the receiver, and neglecting interference, the signal-to-noise ratio (SNR) in dB follows [14]:

$$(5) \quad SNR = EIRP \text{ (dBW)} + \frac{G_r}{T} \left( \frac{\text{dBi}}{\text{K}} \right) - FSPL \text{ (dB)} - AtmLoss \text{ (dB)} - AdLoss \text{ (dB)} - B_w \text{ (dBHz)} - k_B \left( \frac{\text{dBW}}{\text{Hz}} \right) SNR = EIRP + \frac{G_r}{T} - FSPL - AtmLoss - AdLoss - B_w - k_B$$

where  $G_r/T$  is the reception's antenna figure of merit that takes into account both reception Gain (dBi) and Noise Temperature (Kelvin). As an example, the following list gives an overview of typical terminal equipment and their figures of merit:

- 3GPP Class 3 UE, with 0 dBi antenna gain (linear polarized), 200 mW (i.e. 23 dBm) transmission power and 7 to 9 dB Noise Figure. Assuming  $NF = 7 \text{ dB}$  and ambient temperature  $T_{ref} = 290 \text{ K}$ , the noise temperature is  $T = 1163.4 \text{ K}$ , and  $G_r/T = 0 \text{ dBi} - 10 \log_{10}(1163 \text{ K}) = -30 \text{ dB/K}$  at the receiver.
- Very Small Aperture Terminal (VSAT) with 12 dBi antenna gain (circular), 2 W transmission power and 5 dB Noise Figure. In this case, at the receiver  $G_r/T = 12 - 10 \log_{10}(627 \text{ K}) = -16 \text{ dB/K}$  at the receiver.
- IoT devices with 0 dBi antenna gain, 290 K noise temperature and transmission  $EIRP = 23 \text{ dBm}$ . The resulting  $G_r/T = -24.6 \text{ dB/K}$  at the receiver.

Concerning  $FSPL$ ,  $AtmLoss$  and  $AdLoss$ , these refer to Free-Space Path Loss, Atmospheric Loss (due to gases, rain fade, etc) and any other Additional Loss respectively.  $FSPL$  is computed as follows:

$$(6) \quad FSPL = 10 \log_{10} \left( \frac{4\pi df}{c} \right)^2$$

where  $f$  is the transmission frequency (as shown in Table 1) and  $d$  is the slant range, given by:

$$(7) \quad d = -R_E \sin(\alpha) + \sqrt{R_E^2 \sin^2(\alpha) + h_s + 2R_E h_s}$$

where  $R_E$  refers to the Earth radius (6,371 km),  $h_s$  is the satellite height/altitude and  $\alpha$  is the elevation angle. The slant range  $d$  is the distance from the user device to the satellite and can be often approximated by the satellite's orbit. The atmospheric and additional losses take into account the attenuation due to absorption of different molecules in the atmosphere, mainly oxygen and water. Rain fade and availability, not taken into account in eq. 5 accounts for the attenuation due to traversing clouds, rain, etc, which may reduce the availability of the links below 99%. In this sense, the Crane model is often used to estimate these attenuation values on different weather environments (Tundra, Taiga, Maritime, Continental, etc) [3]. Typically, link budget calculations

consider clean sky assumptions (i.e. null attenuation due to rain and fading), but a margin value between 2 and 10 dB are often recommended to compensate from rain fading.

**Numerical example:** Consider a satellite link between a ground station and a LEO satellite operating at  $h_s = 600$  km with elevation angle  $\alpha = 45^\circ$  (or  $\pi/4$  rads). In this setting, the slant range (distance) between transmitter and receiver is  $d = 780.91$  km. The satellite transmits in the S-band (2 GHz) using a 1 MHz bandwidth channel (or 60 dBHz). The satellite's transmission antenna has EIRP = 34 dBW/MHz and the receiving ground station is 3GPP Class 3 UE, that is:  $G_r/T = -30$  dB/K. The FSPL = 78.15 dB and let atmospheric and additional losses account for another 9.6 dB. Following eq. 5, the SNR for this setting is:  $SNR = 34 + (-30) - 78.15 - 9.6 - (-228.6) = 20$  dB or  $snr = 100$  in natural units; that is, the signal power is two hundred times higher than the noise power. This translates into an spectral efficiency of 4.4 bps/Hz, as shown in the next section.

## 2.4. Bitrates, Shannon's capacity limit and Adaptive Coding and Modulation

After a given SNR is obtained from the link-budget analysis following eq. 5, this value together with the bandwidth used for transmission provides an upper bound of the maximum achievable bit rate  $R_{max}$ , as it follows from the Shannon-Hartley's theorem:

$$(8) \quad R_{eff} < R_{max} = B_w \log_2(1 + snr) = B_w \beta_{max}$$

where the effective bitrate  $R_{eff}$  used in transmission cannot be larger than the Shannon's limit  $R_{max}$ . The value  $\beta_{max}$  (in bps/Hz) is often referred to as spectral efficiency (SE) and measures how much bitrate can be obtained from a given bandwidth. Also:

$$(9) \quad \beta_{eff} < \beta_{max} = \log_2(1 + snr)$$

Typical spectral efficiency values range between 0.5 and 2 bps/Hz, reaching even up to 4 bps/Hz in some specific scenarios. Above 5 bps/Hz is often very difficult to achieve in satcoms.

Taking the Shannon's limit the other way around, the communications link must provide sufficient SNR above the minimum required for a given spectral efficiency:

$$(10) \quad snr_{eff} > snr_{req} = 2^{\beta_{max}} - 1$$

It is often recommended that a designed SNR provides a margin of a few dB above the Shannon's limit  $SNR_{req}$  as a rule of thumb, to account for unexpected situations with SNR drop (atmospheric conditions, etc).

Ideally, in the case of absence of noise, the spectral efficiency  $\beta$  would only depend on the modulation used, its coding and reception filter roll-off. However, in the presence of noise, each modulation and coding scheme provides a different spectral efficiency as long as a minimum SNR is guaranteed. Table 2 shows the SNR requirements to achieve Quasi-Error Free (QEF) for some classical modulation and coding schemes (MODCOD) used in satellite links [2]. As shown, low-order

modulations like APSK are less efficient in terms of bits/symbol than higher-order ones, but their SNR requirements are also smaller. Here, QEF refers to bit error rate values of  $10^{-10}$  or above.

MODCOD	SE (bps/Hz)	SNR for QEF (dB)
APSK 1/2	0.4	-2
CPSK 1/4	0.5	0
CPSK 1/2	0.6	1
CPSK 3/4	0.65	2
DPSK 1/4	0.75	3
DPSK 1/2	0.9	4
DPSK 3/4	1.05	6
DPSK 5/6	1.25	7
DPSK 7/8	1.5	9

Table 2. MODCOD table for a theoretical DVB modem, based on Shannon's limit [2].

Typically, modems have a wide range of available modulation and coding (MODCOD) schemes that can be used depending on the SNR link budget, which can be dynamically adjusted depending on the conditions of the satellite link.

## 2.5. Increasing capacity with multiple beams per satellite and frequency reuse

At present, at least four major private companies (Amazon Kuiper, OneWeb, Telesat and Starlink) are in the process of deploying large LEO satellite constellations with hundreds (even thousand) satellites at few hundred km above Earth surface, as summarised in Table 3.

	Shell	Height (km)	Orbits	Sats/orbit	Inclination
Starlink	S1	550	72	22	53°
	S2	110	32	50	53.8°
	S3	1130	8	50	74°
	S4	1275	5	75	81°

	S5	1325	6	75	70°
Kuiper	K1	630	34	34	51.9°
	K2	610	36	36	42°
	K3	590	28	28	33°
Telesat	T1	1015	27	13	98.98°
	T2	1325	40	33	50.88°

Table 3. Constellation for Starlink, Kuiper and Telesat [12]

The footprint area  $A_{sat}$  of one single satellite is obtained from the satellite diameter coverage  $D_{sat}$ :

$$(14) \quad D_{sat} = \frac{P_{Earth}}{N_{orbit}} \quad \text{and} \quad A_{sat} = \pi \left( \frac{D_{sat}}{2} \right)^2$$

where  $P_{Earth} = 40,075$  km and  $N_{orbit}$  are the Earth perimeter and number of satellites per orbit. For instance,  $A_{sat} = 626$  km<sup>2</sup> for a typical 64 satellites per orbit configuration. The number of orbits is typically in the range between 32 to 64, this leads to configurations of hundreds or thousand satellites per constellation.

**Numerical example:** Consider Shell S1 of Starlink, with 22 satellites per orbit. This means that each satellite covers a diameter of  $D_{sat} = 1821.6$  km of diameter. The area/footprint covered per satellite is then  $A_{sat} = 2.6 \times 10^6$  km<sup>2</sup>. Since the total Earth surface is  $510.1 \times 10^6$  km<sup>2</sup>, then the 22 satellites cover only 11% of the total Earth surface. Subsequent shells complement the Earth covered.

Each LEO satellite is often equipped with multiple beams pointing at different regions in its area footprint. This can be achieved in multiple ways, a typical one is by using phased array antennas with high directivity. Indeed, High or Very-High Throughput Satellites (HTS/VHTS) represent an evolution of satellites towards higher capacity through more spot beams and higher frequency reuse. These, applied in LEO orbit constellations, can further provide high bandwidth and reduced latency to enable Mobile Broadband (MBB) and Machine-Type Communications (MTC) in places where both fibre and 5G connectivity has limitations (deep rural areas, sea-side, mountains, etc). V/HTS can be identified by two key technological features [6]:

- The use of multiple spot beams (tens, even hundreds) of narrow beams covering a small geographical area cells, as shown in Fig. 1.
- The frequency reuse of allocated bandwidth in non-adjacent beams/cells, thus higher throughput of the satellite.

Essentially, more capacity can be provided to a given region by partitioning it into smaller sub-regions or cells covered by individual spot beams and leveraging frequency reuse. In this sense, capacity can scale up in the same way as in mobile networks by re-using multiple times the same frequency on non-adjacent cells, while keeping the the Signal to Noise and Interference Ratio (SINR)

under acceptable limits for digital communications. Thus, the total satellite capacity  $R_{tot}$  scales with the number of beams as:

$$(15) \quad R_{tot} = \beta B_w \left( \frac{N_p N_b}{N_c} \right) (1 - \eta_{guard})$$

where  $N_p$  stands for the number of polarizations (1 or 2),  $N_b$  is the number of spot beams (several tens, even hundreds for VHTS),  $N_c$  is the number of colors or frequencies (3, 4 or 6 typically), and  $\eta_{guard}$  is the guard-band between sub-bands (often a value between 5 – 10%).

**Numerical example:** Consider a satellite operating in the Ku-band with 1.5 GHz bandwidth and spectral efficiency of 2 bps/Hz. Under the assumption of 2 polarizations, 7 colors and 60 spot beams, the total capacity delivered by this satellite in the Service link is up to  $R_{tot} = 46$  Gb/s.

Indeed, in the Ku and Ka bands, bandwidth values per spot beam of 1.5-2 GHz are possible. With 1.5 GHz of bandwidth and 2 bps/Hz SE, capacity can be delivered as 1.3-2 Million USD per Gb/s. The largest Ka-band satellites are Jupiter-2 and ViaSat-2, offering total aggregate capacity values of 200 to 300 Gb/s.

However, it is worth remarking that using multiple spot beams on-board heavily increases the size and weight of the satellite. For instance, a one hundred spot beams may account for 2,000 Kg of mass [17]. As a rule of thumb, one Kg of weight can cost around 60,000 USD to get it in the sky. In this light, scaling HTS satellites to VHTS is cost effective since the cost per Gb/s decreases as a power-law in these types of satellites, empirically [6]:

$$(16) \quad Cost = 167.3(R_{tot})^{-0.886}$$

In general, when using multiple beams, different beams may interfere adjacent ones in the frequencies operation. The final Signal to Interference and Noise Ratio (SINR) is obtained from the Signal to Noise and Signal to Interference Ratios (SNR and SIR respectively) as:

$$(17) \quad SINR = \frac{S}{N+I} = \frac{1}{\frac{1}{SNR} + \frac{1}{SIR}}$$

For instance, if the SNR is 9 dB (i.e. 8 times stronger the the signal than the noise power) but the SIR is only 6 dB (i.e. 4 times stronger the signal than the interfering adjacent signals), then the combined SINR reduces to 2.67 times or 4.25 dB. Thus, the network designer must be careful at balancing both noise and interference to not reach important signal degradation. Essentially, the antennas are designed with high directivity to well illuminate a given cell, while the sidelobes that may appear in neighbouring cells are well below the main lobe, typically below 10 dB. In this light, a given cell may receive power from other interfering cells, but the interfering power should be very low. If the SIR is 12 dB, then the previous example gives  $SINR = 5.14$  dB.

To achieve highly directive antennas on board, either linear or planar arrays of  $N$  elements are often employed. For the classical Standard Linear Array (SLA) with  $N$  equally-spaced radiating elements equally spaced  $\lambda/2$ , then the maximum directivity is equal to:

$$(18) \quad D_{SLA} = N$$

For planar rectangular arrays with  $N$  elements again  $\lambda/2$  spaced, the maximum directivity is:



$$(19) \quad D_{SLA} = N\pi$$

It is worth remarking that the Effective Aperture of any antenna system is related with the maximum directivity as:

$$(20) \quad A_e = \frac{\lambda^2}{4\pi} D$$

In planar arrays, the Half-Power Beam Width (HPBW) used in the cellular design is related with directivity as:

$$(21) \quad D \approx \frac{32400}{\theta_{HPBW1D} \theta_{HPBW2D}}$$

where  $\theta_{HPBW1D}$  and  $\theta_{HPBW2D}$  are the angles (in degrees) where power drops 3 dB (or one half). Table 4 shows some examples of linear and planar arrays directivity and HPBW for different number of elements N. All cases assume untapered phased arrays, that is, uniformly weighted.

Antenna	Directivity	HPBW
Linear N=3	3 (or 4.7 dBi)	104°
Linear N=7	7 (or 8.4 dBi)	68°
Linear N=11	11 (or 10.4 dBi)	54°
Planar 4x4	16π (or 17 dBi)	25°
Planar 8x8	64π (or 23 dBi)	12.7°
Planar 16x16	256π (or 29 dBi)	6.4°
Planar 32x32	1024π (or 35 dBi)	3.2°

Table 4. Directivity and HPBW for different antenna arrya configurations.

Numerical example no. 8: Consider the case of a LEO satellite operating at 500 Km altitude, willing to have on board multiple antenna beams, each beam covering an area of 7854 Km<sup>2</sup> (that is, a circle with radius R = 50 Km or 100 Km of diamater). Then, the HPBW of the antenna to illuminate that area should be:

$$HPBW = 2 \tan^{-1} \left( \frac{R}{h_s} \right) = 11.4^\circ$$

Thus, looking at Table 4, the designer should employ an 8x8 Planar Array antenna. Such an antenna has a directivity of 23 dBi on the center of the cell, and 3 dB less at the borders, i.e 20 dBi.

Indeed, the directivity of the beams play an important role to properly cover its cell and not interfere adjacent ones where the same frequency is reused. Directivity increases with the number of antenna elements N, but also Side-Lobe Levels (SLL) reduces as N grows, thus producing less interference in neighbouring cells. For instance, the SLL for a linear array with N = 3 elements is 0.35 (i.e. -5 dB), while for N = 10 is 0.22 (i.e. -6.6 dB). Typical SLL in modern phased arrays with high directivity often start on -10 dB onwards.

It is finally worth remarking that the gain of an antenna is typically smaller than its directivity by a factor  $k_{ef}$  smaller than one:

$$(22) G = k_{ef}D$$

where efficiency  $k_{ef}$  accounts for the ratio of power effectively radiated to the air divided by the input power to the antenna (i.e. not all incoming power into the antenna is transformed into signal).

### 3. Analysis of 3GPP Release 17 integration with NTN segment (State of the Art)

The 3GPP completed the standardization of the first global 5th generation (5G) wireless technology in its Release 15 in mid-2018, the first evolution step of the 5G system was finalized in Release 16. In Release 17, the 3GPP is working on a further evolution to support non-terrestrial networks (NTNs) has been one direction under exploration in 3GPP.

NTN comprises networks that involve non-terrestrial flying or airborne objects, including satellite communication networks, high altitude platform systems (HAPS), and air-to-ground networks. HAPS are airborne platforms which can include airplanes, balloons, and airships.

5G New Radio (NR) based NTN has been one of the main interests in 3GPP [22]. NR was designed to support for low latency, advanced antenna technologies, and spectrum flexibility including operation in low, mid, and high frequency bands. NTN is especially conceived to give support to massive Internet of Things (IoT) use cases using narrowband IoT (NB-IoT) and Long-Term Evolution (LTE) for machine type communication (LTE-M).

#### 3.1. Radio Access Networks for New Radio within the context of NTN

One of the first objectives in 3GPP Release 15 was to select a few reference deployment scenarios of NTN and agree on key parameters such as architecture, orbital altitude, frequency bands, etc. The key scenarios and models include:

- Two frequency ranges, S-band and Ka-band.
- GEO satellites, LEO satellites, as well as HAPS.
- Earth-fixed beams (i.e., beams that are steered towards an area of earth as long as possible) and moving beams (i.e., beams that move over the Earth's surface following the motion of the satellite).
- Typical footprint sizes and minimum elevation angles for GEO, LEO, and HAPS deployments.
- Two types of NTN terminals: handheld terminals and Very Small Aperture Terminals (VSAT) (equipped with parabolic antennas and typically mounted on buildings or vehicles).
- Antenna models for the satellite and HAPS antennas.

A second important objective has to do with NTN channel model, including scenarios for urban, suburban and rural. For instance, multipath is a typical phenomenon in terrestrial propagation environments, but for NTN, the large distance to the satellite causes different paths to be almost parallel. Many of large-scale parameters (line-of-sight probability, angular spread, delay spread, etc.) depend on the elevation angle of the HAP or satellite. Modeling of the path loss mainly relies on free-space path loss but adds components for clutter loss and shadow fading to account for the attenuation by surrounding buildings and objects. Values for clutter loss and shadow fading are tabulated for different elevation angles and for the two frequency ranges of S-band and Ka-band.

In Release-16, the 3GPP focused on the strategies for adapting NR to support NTN. For the User Plane, the main impact comes from the long propagation delays in NTN. Accordingly, the impact of long delays on medium access control (MAC), radio link control (RLC), packet data convergence protocol (PDCP), and service data adaptation protocol (SDAP) were studied. It was concluded that MAC enhancements would be needed for random access, discontinuous reception (DRX), scheduling request, and hybrid automatic repeat request (HARQ). For the CP, the focus of the study was on mobility management procedures, due to the movements of NTN platforms, especially LEO satellites.

Concerning the physical layer perspective, with appropriate satellite beam layouts, handheld user equipment (UE) can be served by LEO and GEO in S-band and that other UE with high transmit and receive antenna gains (e.g., very small aperture terminal (VSAT) and UE equipped with proper phased array antenna) can be served by LEO and GEO in both S-band and Ka-band. In general, NR functionalities form a good basis for supporting NTN, despite issues due to long propagation delays, large Doppler shifts, and moving cells in NTN. However, enhancements in the areas of timing relationships, uplink time and frequency synchronization, and HARQ are required.

Release-17 defined enhancements for LEO and GEO based NTNs and also HAPS and air-to-ground networks. This involves the physical layer aspects, protocols, and architecture as well as the radio resource management, RF requirements, and frequency bands to be used. Transparent payload architectures were assumed with earth fixed tracking areas and frequency-division duplexing (FDD) systems where all UEs are assumed to have global navigation satellite system (GNSS) capabilities. Essentially, a UE with GNSS capabilities can from its position and the NTN ephemeris calculate the relative speed between the UE and the satellite, as well as the round-trip time (RTT) between the UE and the satellite. From the relative speed the UE can calculate and apply a pre-compensation for the doppler frequency to ensure that its uplink signal is received at the satellite or at gNB on the desired frequency.

The transmissions in Rel-16 NR are based on up to 16 stop-and-wait HARQ processes for continuous transmissions. A HARQ process cannot be reused for a new transmission until the feedback for the previous transmission is received. With long RTTs and using stop-and-wait protocol, the transmissions will stall when all HARQ processes are waiting for feedback, which reduces communication throughput. To mitigate the stalling, the number of HARQ processes is extended to 32 which can cover some air-to-ground scenarios. The 32 HARQ processes are however not enough to cover the RTTs of LEO and GEO based NTNs, but are sufficient for HAPS.

In NTN with long RTTs, some of the MAC and RLC timers are extended. As the satellites move, there is a need for the UE to (re)select a new satellite, which is based on the existing criteria and may include new criteria such as the timing when a satellite stops covering the area where the UE is located.

## 3.2. Services and system aspects for NR NTNs

### Services and requirements

The 3GPP SA working group 1 (SA1) is responsible for the overall system requirements for 3GPP systems, including the use cases and service requirements for using satellite access and HAPs in 5G. The main use cases identified in TR 22.822 involved the use of satellites as both access technology for UE in remote areas and as backhaul links between a terrestrial BS and a core network (CN). The former includes broadcast services to provide coverage, for instance for IoT devices and mission-critical access in disaster situations. For the satellite backhaul scenarios, use cases include, for example, fixed backhaul between a BS in a remote area and a CN, as well as backhaul between a moving BS deployed on a train and a CN.

### Architecture

The 3GPP SA working group 2 (SA2) is in charge of the overall system architecture of 5G systems, by identifying the main network functions, how these functions are linked to each other, and the information they exchange.

The SA2 study investigated the impact of supporting satellite access and backhaul on 5G systems. The study aimed to reuse existing solutions defined for terrestrial 5G networks, including the 5GC network, and identified potential differences in functional behaviors and interfaces compared to terrestrial NR. The study concluded that the 5GC architecture is well prepared to support NR NTN access with small enhancements, such as adjusting the quality of service (QoS) framework and introducing new radio access technology (RAT) type values.

The potential complications arising from non-GEO satellites with moving cells were also discussed, and the study suggested that the access and mobility management function (AMF) may need to verify that the UE is located in an area (country) where the AMF is allowed to serve. The study also highlighted the need for some adjustment to existing 5G QoS classes or a definition of new 5G QoS classes, especially when using a GEO satellite with a significant contribution to the end-to-end delay.

In conclusion, the study found that the 5GC is well prepared to support NR NTN access and satellite backhaul with small enhancements. SA2 is currently working on producing the normative specifications for Rel-17, including satellite aspects.

### Telecom Management

SA5 is responsible for management, orchestration, and charging for 3GPP systems. In 2019, the group started a study on management and orchestration aspects with integrated satellite components in a 5G network. The study aimed to reuse existing business models, management, and orchestration of

the current 5G network to minimize the impact and included use cases as well as potential requirements and solutions for management and monitoring of gNB components and network slice management.

The study found that self-organizing networks (SONs) for 5G would need to be enhanced to support mobile non-terrestrial gNBs, and performance measurements that use the HARQ process may be unavailable when using satellite RAN with long delays. The study also suggested that monitoring functions supporting the use of load balancing between different radio technologies should be extended to cover load balancing between terrestrial RAN and non-terrestrial RAN. The work continues in Rel-17, with additional impact to be identified.

Technical Specification Group	Release	Study Item/Work Item	Responsible Groups	Technical Report
RAN (Radio Access Network)	Rel-15	RP-171450: Study on NR to support non-terrestrial networks Objective: study channel model, deployment scenarios, and potential key impact areas.	RAN plenary, RAN1	TR 38.811
	Rel-16	RP-190710: Study on solutions for NR to support non-terrestrial networks Objective: study a set of necessary features enabling NR support for NTN.	RAN1, RAN2, RAN3	TR 38.821
	Rel-17	RP-201256: Solutions for NR to support non-terrestrial networks Objective: specify the enhancements identified for NR NTN with a focus on LEO and GEO and implicit compatibility to support high altitude platform station and air-to-ground scenarios.	RAN1, RAN2, RAN3, RAN4	n/a
	Rel-17	RP-193235: Study on NB-IoT/eMTC support for NTN Objective: identify scenarios and study necessary changes to support NB-IoT and eMTC over satellite.	RAN1, RAN2	TR 36.763
	Rel-17	RP-211573: WID on NB-IoT/eMTC support for NTN Objective: specify support of NB-IoT and eMTC over NTN.	RAN1, RAN2, RAN3	n/a
SA (Service & System Aspects)	Rel-16	SP-170702: Study on using satellite access in 5G Objective: identify use cases and the associated requirements.	SA1	TR 22.822
	Rel-17	SP-180326: Integration of satellite access in 5G Objective: specify stage 1 requirements.	SA1	n/a
	Rel-17	SP-181253: Study on architecture aspects for using satellite access in 5G Objective: identify key issues of satellite integration in 5G system architecture and provide solutions for direct satellite access and satellite backhaul.	SA2	TR 23.737
	Rel-17	P-191335: Integration of satellite systems in the 5G architecture Objective: produce normative specifications based on the conclusions identified in TR 23.737	SA2	n/a
	Rel-17	SP-190138: Management and orchestration aspects with integrated satellite components in a 5G network Objective: identify key issues associated with business roles, service and network management, and orchestration of a 5G network with integrated satellite component(s) and study the associated solutions.	SA5	TR 28.808
	Rel-18	SP-191042: Guidelines for extra-territorial 5G systems. Objective: study use cases of extra-territoriality, identify relevant features, technical aspects, and applicable types of regulations.	SA1	TR 22.926
CT (Core Network & Terminals)	Rel-17	CP-202244: CT aspects of 5GC architecture for satellite networks Objective of study phase: study the issues related to PLMN selection and propose solutions. Objective of normative phase: support the stage 2 requirements, and the requirements and solutions for PLMN selection for satellite access.	CT1, CT3, CT4	TR 24.821

Fig. 3. A summary of activities in 3GPP Re-15, Rel-16 and Rel-17 within the NTN context [23]

### NTNs for IoT applications

In Rel-13, 3GPP specified LTE-M and NB-IoT to support massive machine type communications (mMTC) with low UE complexity, long UE battery life, and coverage enhancements. In Rel-17, 3GPP

has completed a study on IoT NTN and is addressing the minimum necessary specifications for adapting LTE-M and NB-IoT to support NTN. The study aims to identify scenarios applicable to both LTE-M and NB-IoT, recommend necessary changes to support satellite access, and study aspects related to random access procedure and signals, HARQ operation, timers, mobility, and system information.

The study assumes that both LTE-M and NB-IoT devices have GNSS capability, and the impact of GNSS position fix on UE power consumption will be studied. The study also considers the impact of long round-trip time (RTT) and the need to perform GNSS measurements on timing relationships. For mobility, cell selection/re-selection mechanisms of LTE-M and NB-IoT are used as baseline for idle mode mobility, and potential enhancements for conditional handover are to be considered for both moving cell and fixed cell scenarios.

## 4. Algorithms for efficient fault-tolerant switching tables (State of the Art)

The use of terrestrial technologies in space enables significant cost reductions as they only need to be adapted and not redone from scratch. This is needed as the development of advanced devices only for space has a cost that grows exponentially with the technology node at the nanometer scale. In the case of networks, Ethernet is an attractive technology for spacecraft networks as it provides a large number of options for transceivers and features, combined with high maturity and a large number of components' providers [24].

However, the original Ethernet lacked some features to support the time-critical operations that are needed for some functions on a spacecraft [25]. This has been addressed with the development of Ethernet-based solutions such as Time-Triggered Ethernet (TTE) [25] and later with the Time Sensitive Networking (TSN) capabilities added in recent Ethernet standards [26]. Those solutions are able to provide delay guarantees for critical traffic while supporting the integration of all types of traffic on the same network [27]. Time-Triggered Ethernet (TTE) has been for example adopted in several space launchers [28],[29].

Another fundamental issue when adopting terrestrial technologies in space is the need to withstand a more adverse environment, and in particular to be exposed to radiation that can cause errors and failures on electronic components [30]. Space components are commonly hardened to avoid or mitigate the effects of errors. In the case of Ethernet different hardening approaches have been explored for example for Ethernet transceivers [31],[32]. The effect of radiation-induced errors on routers and switches has also been studied [33],[34].

In order to enable high-speed and scalable networks in spacecraft, error tolerance has to be implemented at low cost in terms of area and power consumption. In the following sections, we first briefly describe the main blocks in a router and then we review existing schemes to implement fault tolerance in the different blocks of a router with the aim of providing a vision of the state of the art

in this topic. As part of this work, we identify areas with potential for innovation that will be explored in the next phase of the project.

#### 4.1. Structure of switches

The structure of a switch may be different depending on its features and on the platform used for implementation. For a hardware implementation, the typical structure of a shared memory switch is shown in Figure 4. The main elements are the logic and buffers in the ports, the shared buffer, and the decision logic. The telemetry, control, and management are in many cases implemented in software on a processor embedded in the switch [35].

The buffers both the shared one and those in each port, store packets that are being processed, waiting to be read by the outgoing port or to be transmitted by that port. In addition to the packets they also store metadata needed to process the packets. Instead, the decision logic is formed by hash tables or similar data structures and Content Addressable Memories (CAMs) used to find the outgoing port for each packet. Together they account for the majority of the switch area in most designs.



Fig. 4. Block diagram of a shared-memory switch.

In the following, we discuss the protection of buffers and decision logic as they are the main elements of the switch and also because for the management and control, as it is implemented in software, standard protection techniques can be used for the processor and or for the software.

#### 4.2. Protection of buffers

The protection of the buffers is commonly implemented by using memories protected with error correction codes [36]. This introduces significant overhead, especially when errors are not only detected but corrected. The use of an error correction code for the protection of a memory is shown in Figure 2. The data is first encoded by adding a number of parity bits when writing into the memory. Then on a read those bits are checked to detect and correct errors. Therefore, the use of an error correction code requires having additional bits per memory word which introduces a significant overhead in terms of area and power consumption.

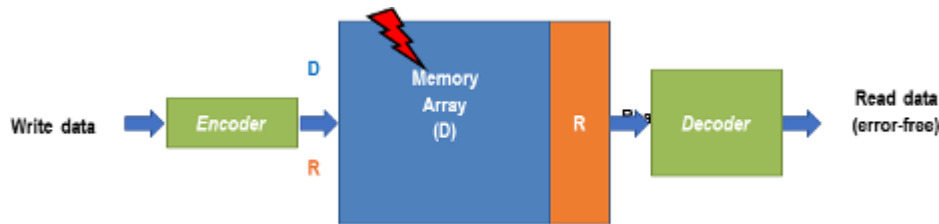


Fig. 5. Protection of a memory with an error correction code.

An interesting observation is that packets already have an error detection code, typically a cyclic redundancy check to detect errors in transmissions that could be potentially leveraged to detect errors in memories [35]. The problem is that metadata still needs to be protected as it is not included in the cyclic redundancy check. Exploring the use of existing error detection capabilities in the packets and extending them to the metadata added by the switch could significantly reduce the overhead needed to detect errors in buffers.

### 4.3. Protection of decision logic

The implementation of decision logic is more complex and includes in many cases hash-based data structures [37],[38], and content addressable memories [39].

The error detection and correction of content addressable memories have been widely studied for both ASIC [40],[41] and FPGA implementations [39],[42]. However, in modern switch implementations, there is a trend to use hash-based data structures to replace content addressable memories [37]. Therefore, it seems more relevant to consider the protection of hash-based implementations.

The protection of hash-based data structures has also been considered in several works [43],[44],[45] showing that it is possible to implement error detection or correction at low cost. For example, if a hash function that has error detection or correction capabilities is used, the position on which an element is stored can be used to detect and possibly corrected errors on the key associated with that element. This is of interest for space implementations as power consumption is a major issue in spacecraft. In this area, it seems that there can be opportunities to optimize the protection by customizing the protection schemes to the use of these structures in switches. However, existing techniques are only capable of protecting the key used in the hash table but not the values or metadata associated with that element. Therefore, it is of interest to extend the protection to the values without having to use an error detection or correction code that would incur in an additional overhead.



#### 4.4. Areas of innovation

Based on the previous study of the state of the art, we can identify broad areas for innovation to support the implementation of switches and routers in space:

1. The use of the in-packet cyclic redundancy check to detect errors in the packets stored buffers and their metadata.
2. The customization of existing protection techniques for hash-based data structures to their use in switches and routers.

In the next phases of the project those areas will be investigated to propose efficient protection schemes that can detect errors at a fraction of the cost of existing schemes.

### 5. Machine Learning and Deep Learning applied to the space segment and integration of NTN and 3GPP networks (State of the Art)

As previously stated, Non-Terrestrial Networks (NTN) are expected to be a critical component in the deployment of 6th Generation (6G) networks. In NTN, satellites are the primary enabler (but not the only one), as they provide extensive coverage, stable orbits, scalability, and adherence to international regulations. However, satellite-based NTN presents unique challenges, such as long propagation delay, high Doppler shift, frequent handovers, spectrum sharing complexities, and intricate beam and resource allocation. The integration of NTN into existing terrestrial networks in 6G introduces a range of novel challenges, such as task offloading, network routing, network slicing, and many more. AI/ML techniques can provide solutions to many of these research challenges, for instance by capturing patterns among collected data and using the data to both predict and interpret the behaviour of the NTN.

Indeed, AI is having a profound impact on many industries, including healthcare, military, transportation, and e-commerce. In addition to this, ML is a subset of AI that allows machines to learn from data and make decisions without being explicitly programmed for that particular task, only it uses data to generate models of a given outcome and generalises from that data to efficiently solve the task on new unseen cases. Deep learning (DL) is a special subset of ML that uses artificial neural networks to learn from data, and is specially focused on applications involving computer vision, speech recognition, and bioinformatics.

In the mobile and satellite communications, AI/ML techniques are still in their infancy in terms of integration but they have a tremendous potential to address many challenges associated to the space segment. However, there are practical implementation difficulties that need to be addressed before AI can be fully deployed in 6G networks. To reach optimal performance, theoretical

advancements in communication system design must be complemented by appropriate AI solutions. A summary of the applications of AI/ML techniques for NTN networks is overviewed next.

### 5.1. AI/ML techniques for mobile services in NTNs

Concerning moving cell connectivity, the authors in [46] discuss the challenges of deploying a reliable transport service, particularly in high-speed scenarios like airplanes or trains. It suggests considering Low Earth Orbit (LEO) or High Altitude Platform Stations (HAPS) as Non-Terrestrial Entities (NTEs) to address the problem. Reinforcement Learning (RL) and the Q-learning algorithm can be used to dynamically adjust the position of HAPS to maximize network capacity and minimize transmission latency. The trajectory planner must account for user numbers, service requirements, and trajectories to position the HAPS properly. RL-based approaches are also used to control disconnection time and handover rate, leading to a 50% reduction in handover rate compared to traditional strategies. This RL-powered handover rate reduction could also benefit other Non-Terrestrial Networks (NTNs), allowing various optimizations between NTEs like LEO and HAPS.

Furthermore, the authors in [47] discuss the applicability of reinforcement Q-Learning techniques in service provisioning for isolated and remote areas. Unmanned Aerial Vehicles (UAVs) can be employed in this scenario, but energy resource management becomes crucial. RL can assist in scheduling ground User Equipment (UE) to minimize the Age of Information (AoI) and energy consumption. Additionally, ground-air multi-access edge computing (MEC) with low-power mMTC sensors can optimize computation offloading based on task resource requirements. The study [47] demonstrates the use of a fully distributed game-based ML algorithm to achieve Nash equilibrium without information exchange, resulting in better offloading strategies and overall performance. The work considers average response time and energy consumption as performance metrics and shows that ML can reduce the average cost per device by 50-60% compared to random or traditional offloading strategies.

Network throughput can also be improved with the help of AI/ML techniques. Firstly, dedicated Non-Terrestrial Entities (NTEs) can be used to increase network capacity temporarily, enhancing the quality of experience (QoE) for users. During outdoor events, UAVs can be deployed above crowded areas and aid in content caching/storage, significantly reducing latency compared to remote cloud servers. ML, especially RL, can assist in 3D positioning of UAVs and optimize caching decisions based on estimated future user requests. Secondly, multi-connectivity is proposed to maximize throughput in a hybrid NTN/TN environment. RL algorithms can learn to select the best transmitter combination among terrestrial (gNB) or non-terrestrial (UAV, HAPS, and LEO) entities, considering factors such as NTE and User Equipment (UE) trajectories, congestion estimation of NTEs and gNBs, signal quality received by UEs, and coverage estimation. The RL technique should consider the position of transmitting gNBs (ground, air, or space) and the related latencies on the Xn interface. By leveraging ML optimization, these approaches hold promise for enhancing network performance and user satisfaction.

AI/ML can also be applied to address service outages in Internet communications and improve network reliability. Non-Terrestrial Entities (NTEs) such as UAVs, HAPS, and LEOs can quickly restore

links after failures, but their deployment may take time. ML can shorten downtime by classifying failures, helping network operations resolve issues more efficiently. For instance, a classifier developed using bidirectional forwarding detection (BFD) achieved a 0.99 F1-Score for link failures in [48]. Additionally, radio link outages can be predicted using ML models like LSTM and NN, as shown in [49], with a 0.94 F1-Score performance. In situations where a secondary backup link is deployed to ensure service continuity, ML-based techniques can be employed for load balancing. Traditional methods based on network metrics may be insufficient when multiple UAVs serve as MEC nodes. In [50], a deep RL algorithm is proposed to solve the task scheduling problem among multiple UAVs acting as MEC nodes, serving IoT nodes. The RL-based solution outperforms traditional first-come first-served (FCFS) scheduling, resulting in a 65–75% average slowdown reduction in task completion time. These ML-driven approaches enhance network resilience and performance during outages and load balancing scenarios.

In disaster relief situations, NTEs like UAVs are crucial for providing rapid connectivity to support rescue teams and survivors. Optimizing UAV positioning is essential to maximize coverage, minimize power consumption, and extend flight time. In [51], a combined approach using multi-layer perceptron (MLP) and long short-term memory (LSTM) was proposed to optimize UAV positions based on user service requirements, achieving a 98% user throughput maximization accuracy. UAVs can also serve in search and rescue operations, using computer vision techniques like object detection to spot people and alert rescue teams. Additionally, they can offload computationally expensive tasks like image processing to air-space or terrestrial MEC (Mobile Edge Computing) nodes. Deep learning-based object tracking can be employed to follow rescue teams and not only provide connectivity but also scan the surrounding area for further assistance. These applications of NTEs and ML play a crucial role in disaster relief efforts, facilitating communication, and aiding rescue operations efficiently.

AI/ML algorithms can also play a significant role in optimizing cache performance, particularly in mass content delivery with low response time. Having content at the network edge is crucial for interactive broadcast services. ML frameworks can proactively fetch and push content to the edge based on content popularity, user access, and mobility, reducing delays and network burden during peak hours. Traditional cache replacement techniques like FIFO, LFU, or LRU may not be suitable for non-deterministic scenarios. To address this issue, a (deep) Q-Learning RL network can be applied to make cache replacement/eviction decisions based on Q-Value or rewards obtained from the environment. A study [52] measured system throughput as a function of cluster size under different replacement schemes. The test-bed implementation showed that the adoption of a dynamic RL-powered policy improved throughput by 4-5 times compared to a static policy. These ML-driven caching strategies significantly enhance content delivery efficiency and overall network performance.

Finally, it is of utmost importance to carefully assess the deployment position of a Multi-Access Edge Computing (MEC) in Non-Terrestrial Networks (NTNs). MEC cannot be placed everywhere in the architecture, as it requires network elements capable of reading user IP addresses to route packets and retrieve contents properly [53]. Currently, MEC can be deployed in UPF in the 5G architecture, but deploying it on-board Non-Terrestrial Entities (NTEs) like UAVs can be challenging due to energy

constraints, processing limitations, and storage issues. HAPS or LEO may offer better possibilities for MEC deployment. The MEC platform supports application configuration, managed by the MEC host manager, which sets traffic rules, policies, and resolves conflicts. The MEC system management handles application instantiation for user requests through the MEC orchestrator. To enable connectivity between MECs of different mobile network operators, MEC hosts should be connected through the two MEC platforms. Proper design and consideration of advantages, such as latency reduction, improved throughput, and traffic offload, are essential for successful MEC deployment in NTN environments [54,55].

## 5.2. AI/ML techniques in the physical layer of NTNs

In the physical layer, AI/ML can also produce significant performance improvements as demonstrated in [56], where a Convolutional Neural Network (CNN) called AlexNet is used to classify received signals among different modulation schemes, such as 16QAM and 64QAM. AlexNet outperforms traditional Support Vector Machine (SVM) based techniques, achieving higher accuracy. The accuracy of the classifier varies based on the Signal-to-Noise Ratio (SNR) for different modulation types. While QPSK and 8PSK identification are highly accurate at low SNRs, 16QAM and 64QAM achieve lower accuracy but remain sufficiently accurate (>80%) at SNRs  $\geq 4$  dB. ML is also employed in predicting propagation loss, where deterministic models like ray tracing are more accurate but computationally demanding, while statistical models like Okumura-Hata are less accurate but computationally efficient. To strike a balance, a Neural Network (NN) based procedure is proposed in [57] to predict path loss in an urban environment. The goal is to approximate the ray tracing performance with reduced computation cost. Results demonstrate an accuracy of  $\pm 2.5$  dB for uniformly built-up environments and 4.9 dB for non-uniform environments. These ML-based approaches improve the reliability and efficiency of physical layer operations in communication systems.

## 5.3. AI/ML techniques in the MAC and LLC layers of NTNs

In traditional wireless networks, AI/ML can be used for efficient and proactive spectrum allocation. In [58], a Deep Neural Network (DNN) is adopted to solve the weighted sum-rate maximization problem subject to transmit power constraints in real time. The DNN approximation significantly speeds up computation compared to the traditional weighted minimum mean square error (WMMSE) method. ML models can be used for resource allocation between different Non-Terrestrial Entities (NTEs) or even optimize area throughput by dynamically adjusting the size of LEO beam footprints based on user density, mobility, and traffic type. ML is also applied for User Equipment (UE) traffic prediction, where models like auto-encoders and LSTM units are used for spatial and temporal modeling. The ML-based approach outperforms traditional techniques like support vector regression (SVR) and auto-regression integrated moving average (ARIMA) in terms of prediction accuracy. For Non-Terrestrial Networks (NTNs), ML techniques can be used to address novel issues, such as NTE selection based on network congestion and requested Quality of Service/Experience (QoS/QoE). For example, ML can help choose the NTE with the shortest delay or least congestion to optimize service delivery [59].

## 5.4. AI/ML techniques in the network layer of NTN

Finding the optimal path between nodes in a network can be challenging, especially when dealing with highly varying network conditions like overloaded routers, malfunctions, or outages. Traditional routing algorithms face heavy computation loads to ensure good end-to-end transmission performance, but they may not improve global transmission performance. In Non-Terrestrial Networks (NTNs), routing problems become even more difficult due to the heterogeneous nature of the network. To address these challenges, a supervised learning approach was proposed in [60], aimed at improving routing performance in NTNs. This ML-based approach outperforms the traditional Open Shortest Path First (OSPF) protocol in terms of signaling overhead, throughput, and per-hop delay. Simulation results demonstrated significant improvements: the ML technique reduced signaling overhead by 70%, increased throughput by 2%, and decreased hop-delay by 90%. By leveraging ML, NTNs can achieve more efficient and effective routing, enhancing overall network performance.

## 5.5. AI/ML techniques in the application layer of NTN

In the application layer, AI/ML can also be applied for different types of improvements. One example is internet traffic classification, where ML can streamline the process by performing both feature extraction and classification in one system. A presented system [61] characterizes and identifies specific applications, achieving precision and recall greater than 90% for plain and VPN-encapsulated traffic. In Non-Terrestrial Networks (NTNs), traffic classification can be used to select the appropriate NTE based on application requirements. For instance, when a VoIP call is identified, routing the traffic over UAV or HAPS may be more suitable, leaving GEO satellites for less sensitive applications like unidirectional video streaming.

ML can also optimize data rates at the application level by estimating end-to-end round trip time (RTT). For media streaming services, predicting users' future RTT values can directly improve throughput by adjusting buffering or coding strategies in advance to avoid video quality degradation. Due to fluctuations in RTT caused by air and space elements in NTNs, having advance RTT estimations becomes more critical for implementing suitable countermeasures effectively. These ML-based approaches enhance application performance and user experience in NTNs.

# 6. Conclusions

In 10 years, it is expected that the number of satellites orbiting the Earth will reach 50,000 satellites (i.e., a 20-fold increase), thanks to recent advances in low-cost satellite launches with high success rates. In this regard, the world is expected to witness a massive increase in mobile connectivity in the coming years, combining 5G deployments with satellites, forming what is called the Integrated Space-Terrestrial Network (STIN) through the emergence of Non-Terrestrial Networks (NTNs).

This document has briefly reviewed the fundamentals of satellite communications and the latest advances in fault-tolerant onboard equipment, AI/ML-based applications in STIN, and advancements

and deployments in NTN. Additionally, the document delves into the 3GPP Release 17 standard in the context of NTN and analyzes the state of the art in hardware fault tolerance strategies in the space segment, as well as the applications of AI/ML in optimizing the operation and performance of satellite communications and High-Altitude Pseudo-Satellites (HAPS).

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