CONVERGING EARTH AND SPACE: AI-DRIVEN TN/NTN CONNECTIVITY

By ESA CSC (Connectivity and Secure Communications)
Space for 5G/6G and Sustainable Connectivity

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Editors: Ana Stroescu, Antonio Franchi

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LIST OF ACRONYMS

Acronym	Definition
3GPP	Third Generation Partnership Project
4G	4th Generation
5G	5th Generation
6G	6th Generation
AI	Artificial Intelligence
AR	Augmented Reality
ASIC	Application-Specific Integrated Circuit
AV	Autonomous Vehicle
C-RAN	Cloud Radio Access Network
CPE	Customer Premises Equipment
CSF	Channel State Feedback
E2E	End-to-End
eMBB	enhanced Mobile Broadband
ETSI	European Telecommunications Standards Institute
FL	Federated Learning
FMTL	Federated Multi-Task Learning
GAN	Generative Adversarial Network
GDPR	General Data Protection Regulation
GenAI	Generative Artificial Intelligence
GEO	Geostationary Earth Orbit
GSMA	Global System for Mobile Communications Association
HAP	High-Altitude Platform
IoT	Internet of Things
ITU	International Telecommunications Union
LLM	Large Language Model
ML	Machine Learning
mMTC	massive Machine Type Communications
MPC	Multi-Party Computation
MR	Mixed Reality
MTTR	Mean Time to Repair
MEC	Multi-Access Edge Computing
nGRG	Next Generation Research Group
NTN	Non-Terrestrial Network
NWDAF	Network Data Analytics Functions
O-RAN	Open Radio Access Network
O-RU	Open Radio Unit
PEFT	Parameter-Efficient Fine-Tuning
QLoRA	Quantized Low-Rank Adaptation
QoE	Quality of Experience
QoS	Quality of Service
QKD	Quantum Key Distribution
RAG	Retrieval-Augmented Generation
RAN	Radio Access Network
SDG	Sustainable Development Goals
SNN	Spiking Neural Network
SON	Self-Organising Networks
TN	Terrestrial Network
UAS	Unmanned Aircraft System
UN	United Nations
URLLC	Ultra Reliable Low Latency Communications
V2X	Vehicle-to-Everything
VR	Virtual Reality
XAI	Explainable Artificial Intelligence

1. EXECUTIVE SUMMARY

The telecommunications industry is undergoing a significant transformation, driven by the integration of Artificial Intelligence (AI) across networks. As AI advances, it will become increasingly integral to the design, optimisation, and automation of telecommunications systems; particularly in the context of Terrestrial Networks (TN) and Non-Terrestrial Networks (NTN). This white paper explores the role of AI in shaping the future of telecommunications, with a focus on the integration of AI into various network components, from Radio Access Networks (RAN) to core networks and edge devices. It also highlights the synergies between AI and satellite technologies, emphasising their combined impact on enhancing global connectivity and reducing latency.

The paper delves into AI-driven network optimisation, highlighting key components such as Federated Learning (FL), generative AI, and Network Data Analytics Functions (NWDAF). It also addresses the challenges and opportunities presented by AI in the telecommunications industry, including data privacy, security, and the ethical deployment of AI. A particular focus is placed on the evolution of AI in 3rd Generation Partnership Project (3GPP) standardisation efforts, which are essential for aligning industry-wide practices and ensuring interoperability across diverse networks.

In addition to discussing current applications, this white paper looks forward to the future of AI in networks, particularly in the context of 6G. AI is expected to be a fundamental element of 6G networks by enhancing system performance, enabling automation, and improving the overall user experience. Key hardware advancements such as neuromorphic computing, quantum computing, and AI-optimised chips are explored as essential enablers of AI-native 6G networks.

Furthermore, AI for the cyber-physical world will drive innovations such as digital twins, physics-aware AI, and advanced security protocols, which will ultimately enhance the robustness and intelligence of future telecommunications infrastructures.

As the industry prepares for the next generation of telecommunications, the AI-native approach in 6G will redefine the landscape and create new opportunities for efficiency, flexibility, and intelligence in network management.

This white paper provides a comprehensive roadmap for stakeholders – governments, telecom operators, and technology developers – towards a future where AI plays a central role in the evolution of telecommunication networks. The focus is on fostering collaboration, investing in advanced AI technologies, and developing standardised frameworks to ensure a smooth and secure transition to AI-driven, 6G-enabled telecommunications systems.

2. INTRODUCTION

The integration of AI into telecommunications networks is transforming the industry, with profound impacts on both terrestrial and non-terrestrial networks. Terrestrial networks, comprising traditional land-based infrastructure, are the backbone of global connectivity, while non-terrestrial networks, comprising satellite systems, high-altitude platforms, and Unmanned Aerial Systems (UAS), extend communication capabilities to remote and underserved areas. Together, terrestrial and non-terrestrial networks form a comprehensive communication ecosystem that aims for seamless connectivity across diverse environments.

AI plays a pivotal role in optimising these networks, addressing challenges such as resource allocation, dynamic traffic management, interference mitigation, and security threats. For non-terrestrial networks, the use of AI enhances adaptive network planning in the presence of rapidly changing conditions, such as satellite mobility and atmospheric interference. In terrestrial networks, AI enables efficient operations, robust fault management, and enhanced user experiences. This convergence is crucial for the evolution of 6G networks and beyond facilitating seamless global communication and the expansion of Internet of Things (IoT).

2.1 TELECOMMUNICATIONS IN THE ERA OF AI-DRIVEN TRANSFORMATION

Telecommunications is undergoing a profound transformation driven by the exponential growth in connectivity demands, the proliferation of connected devices, and the increasing complexity of modern networks. A 5G network is 100 times faster than its predecessor, and its low latency provides the quick reaction needed for real-time applications. In 2018, Ericsson predicted that there would be 1.5 billion 5G subscriptions worldwide by the end of 2024.

However, due to the swift adoption and strong consumer interest in the technology, the company revised its estimate to 1.9 billion in 2019[1]. GSMA predicts that 5G has been the fastest mobile generation rollout to date, exceeding one billion connections by the end of 2022 and reaching 1.6 billion by the close of 2023. Approximately 5.5 billion connections are expected by 2030[2].

The International Telecommunication Union (ITU) has identified three major categories of applications that are based on network performance and user Quality of Experience (QoE): enhanced Mobile Broadband (eMBB), massive Machine-Type Communications (mMTC), and Ultra-Reliable Low-Latency Communications (URLLC).

The number of devices that can connect to 5G could exceed that of 4G devices 100-fold, allowing connectivity between Autonomous Vehicles (AVs), smartwatches, drones, Mixed Reality (MR) headsets, and other IoT devices. Moreover, leveraging the large coverage area of satellites, a large number of IoT devices can be effectively supported in mMTC applications. URLLC applications include mission-critical communications that require high-reliability, such as remote medical surgery and telemedicine, which has the potential of lowering the cost of healthcare by $305 billion per year[4].

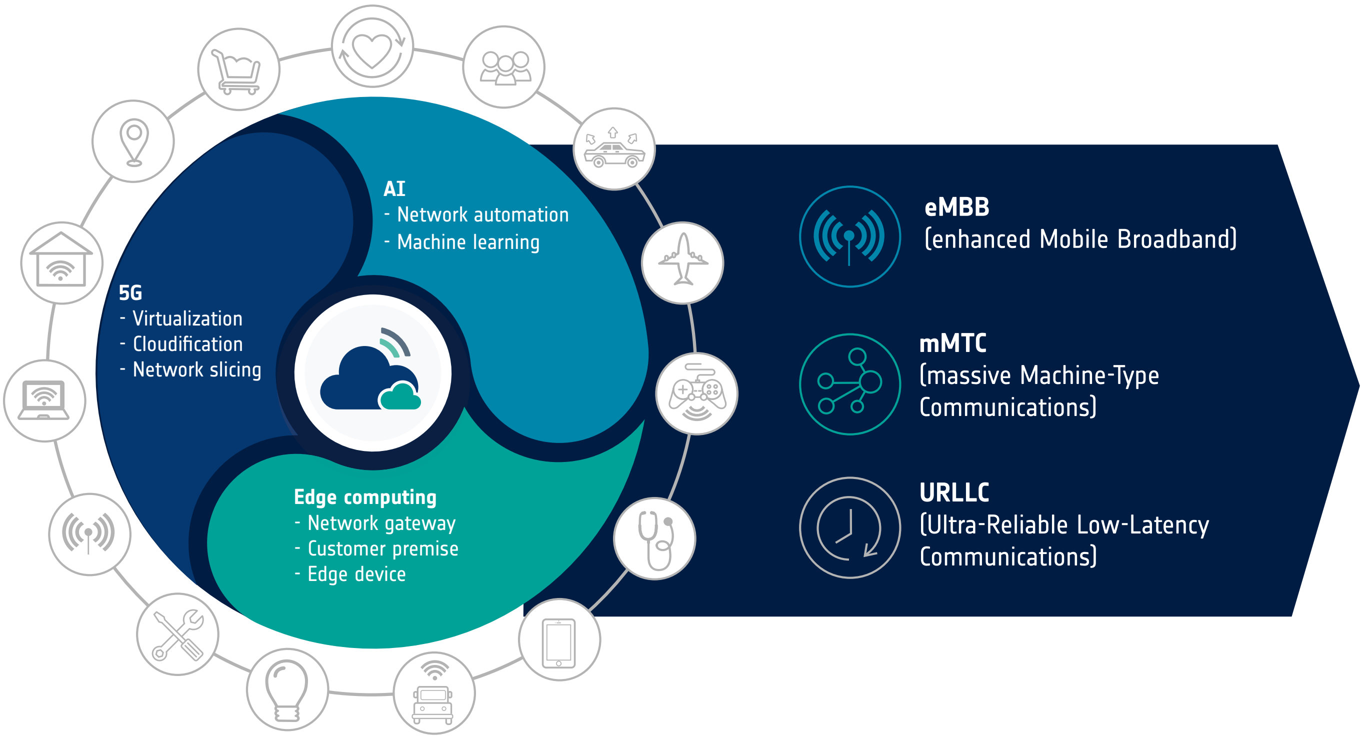


***Fig. 1:** 5G Ecosystem – confluence of 5G, Edge and AI*[3].

By leveraging advanced Machine Learning (ML) algorithms, data analytics, and automation, AI has the potential to reshape the telecommunications landscape by:

- **Automating complex operations**: AI could replace traditional manual processes with intelligent automation, enabling networks to self-manage and adapt dynamically. This allows for significant reduction in human error and the enhancement of operational efficiency. Self-Optimising Networks (SONs) can autonomously adjust parameters, including signal strength, frequency allocation, and routing paths based on real-time network conditions.

- **Enhancing scalability**: AI algorithms have the potential to dynamically adapt to growing network demands, ensuring seamless performance – even as the volume of devices and data increases. AI would use predictive analytics to anticipate network usage trends and scale resources proactively.

- **Optimising resource allocation**: AI could enable precise and real-time adjustments in bandwidth, spectrum, and computational resources for optimal utilisation and reduction of wastage. AI algorithms can be trained to learn network usage patterns and identify underutilised frequency bands to reallocate them to high-demand areas. AI can adjust power usage dynamically, reducing energy consumption and supporting green initiatives in telecommunications.

- **Predictive maintenance**: AI revolutionises network maintenance by shifting from reactive to proactive approaches. Instead of waiting for issues to disrupt operations, proactive diagnostics reduce downtime and operational disruptions by identifying potential issues before they escalate. ML models can be trained on historical data to predict equipment failures, allowing operators to schedule maintenance proactively. The model can predict the root cause of issues, reducing the Mean Time To Repair (MTTR), hence minimising the downtime and enhancing customer QoE.

2.2 AI AT THE EDGE

Edge computing, including Multi-Access Edge Computing (MEC), as defined by the European Standards Organisation and the European Telecommunications Standards Institute (ETSI)[5], complements cloud computing by processing data closer to end-users, reducing latency and network congestion, and enabling latency-critical applications, such as autonomous vehicles and robots, to fully leverage the capabilities of 5G.

AI has become the key driver for the adoption of edge computing[3]. AI at the edge enables rapid data processing and real-time decision-making for critical applications, including machine control, remote surgery, and AI-assisted driving. It improves user experiences, enhances security by analysing sensitive data locally, and reduces reliance on centralised cloud storage.

2.3 SYNERGIES BETWEEN SATELLITE AND AI IN TN/NTN

The satellite communication ecosystem is undergoing a significant transformation, marked by cutting-edge technological advancements that are shaping a new space age. Lower orbits are emerging as a promising low-latency alternative to the conventional Geostationary Orbit (GEO) systems. Most existing satellite communication systems depend heavily on human expertise and manual operations[6], which present two main issues. First, human intervention in system control processes contributes to increased operational expenditure and delays.

Second, the rapidly evolving radio environments in modern space scenarios demand self-adaptive mechanisms that go beyond the limits of manual control. Additionally, the growing variety of applications and services enabled by satellite communication in the near future will generate massive amounts of data. To address this, satellites must be equipped with the ability to autonomously process this data and make reliable, independent decisions[7].

The two primary applications with significant potential for NTN are eMBB and mMTC, driven by the broad coverage area offered by satellites[8]. This capability allows satellite systems to provide connectivity to underserved or unserved regions, such as islands, ships, aircraft, and remote areas, where terrestrial communication infrastructure is either limited or unfeasible. Satellites are essential for ensuring global connectivity, particularly in regions with inadequate terrestrial networks. The integration of AI further enhances their performance by:

- **Beamforming optimisation**: AI adjusts satellite beams dynamically to maximise coverage, enhance signal quality and minimise interference, addressing challenges posed by diverse geographies.
- **Mobility management**: AI ensures seamless and uninterrupted connectivity by intelligently managing handovers between terrestrial and satellite networks.
- **Energy efficiency**: AI-driven optimisation minimises power consumption in satellite operations, contributing to long-term sustainability and significantly reduced operational costs.
- **Advanced traffic analysis**: AI-enabled traffic prioritisation ensures critical applications receive the necessary bandwidth, improving user experience across remote and urban settings.

3. THE INTEGRATION OF AI IN TN/NTN

The integration of AI in terrestrial and non-terrestrial networks lays the foundation for emerging technologies such as IoT, smart cities, and autonomous systems.

3.1 AI IN THE RADIO ACCESS NETWORK (RAN)

RANs connect user devices to the core network and handle radio communication tasks such as signal transmission, resource management, and handovers. AI can leverage vast amounts of data generated by the RAN to make intelligent decisions in real-time, enabling the network to self-organise, self-optimise, and self-heal. This capability is particularly important for managing dynamic network conditions, such as varying traffic loads, interference, and mobility patterns. Specific applications include:

- **Dynamic beam management**:
  AI-driven algorithms dynamically optimise beamforming, increasing throughput and reducing latency, particularly in densely populated urban environments and challenging terrains.
- **Channel State Feedback (CSF)**:
  AI compresses and reconstructs CSF data, enhancing spectrum utilisation while significantly reducing network overhead and latency.
- **Energy-aware RAN operations**: AI identifies patterns in energy consumption and implements adaptive measures to improve the power efficiency of RAN infrastructure.

Traditionally, RANs have relied on proprietary hardware and tightly integrated software, making them inflexible and difficult to optimise. However, modern RAN architectures like Cloud RAN (C-RAN), Open RAN, and O-RAN offer greater flexibility, scalability, and cost-efficiency by enabling centralised, disaggregated, and open network solutions.

3.1.1 AI IN CLOUD RAN (C-RAN)

Cloud RAN (C-RAN) is a centralised architecture where baseband processing functions are moved to a cloud-based data centre instead of being distributed across individual base stations. This approach decouples the hardware from the software and enables the centralisation of processing power, allowing for greater flexibility, scalability, and cost efficiency. AI plays a crucial role in enhancing the capabilities of Cloud RAN by optimising and managing network operations[9-12] using:

- **Intelligent resource management**:
  AI algorithms can predict and dynamically allocate resources based on real-time traffic conditions, ensuring optimal performance across the cloud infrastructure.
- **Load balancing and traffic steering**:
  AI can identify patterns in traffic loads and user behaviour, adjusting network functions to distribute traffic more efficiently across the cloud infrastructure, thus minimising congestion and improving Quality of Service (QoS).
- **Predictive maintenance**: AI can be used to monitor the health of network components, detecting potential failures or anomalies before they cause service disruptions. This enables proactive maintenance and reduces downtime.

3.1.2 AI IN OPEN RAN AND O-RAN

Open RAN and its advanced evolution, O-RAN, are designed to provide flexible, open, and interoperable network architectures. It is here where AI can play a key role in optimising network performance: AI enables real-time management, automation, and efficiency across both Open RAN and O-RAN environments to meet the dynamic needs of modern 5G networks and beyond. Key AI contributions include:

- **Interference mitigation and automation**: AI detects and mitigates interference by dynamically adjusting parameters such as power levels and antenna configurations. It also enables Self-Organising Networks (SON) that can autonomously configure, optimise, and troubleshoot the network, improving efficiency with minimal manual intervention.
- **AI-powered integration and decision-making**: AI automates the configuration and optimisation of RAN components from different vendors, while providing real-time analytics for proactive decision-making – with the aim of improving network performance and reducing operational costs.

In addition to these advancements, the 5G Americas O-RAN white paper[13] highlights several important areas of focus for O-RAN's future, particularly in the context of 6G and beyond.

The O-RAN Alliance's Next Generation Research Group (nGRG) is researching open and intelligent RAN principles that will be essential for the development of 6G networks. These principles emphasise pervasive AI/ML across all domains, cloud-native and sustainable architectures, and enhanced security. Notable research efforts within the O-RAN framework also include:

- **Native AI architecture in O-RAN**: The O-RAN Native AI Architecture reports[14,15] focus on the requirements and general principles of AI in O-RAN, exploring both centralised and distributed AI architectures. This includes the integration of AI with digital twins, core networks, and management domains, while also addressing the need for new interfaces, protocols, and the management of cross-domain AI lifecycles.
- **Spectrum sharing with shared O-RU**: Another critical area of research involves spectrum sharing for better utilisation of this limited resource. The research conducted by O-RAN next Generation Research Group (nGRG)[16] proposes a "neutral host" approach for shared use of Open Radio Units (O-RUs), among multiple operators, to improve spectrum efficiency. This concept extends to public, private, and governmental users and is radio technology agnostic, making it a valuable addition to O-RAN's future capabilities.

3.2 AI IN CORE NETWORKS

AI plays a critical role in optimising and managing core networks within both TN and NTN environments. The core network is responsible for routing, processing, and managing data traffic between different network components and services, making it a central part of the overall network architecture. By integrating AI, core networks can become more intelligent, agile, and capable of handling the complex demands of next-generation services and applications.

3.2.1 NETWORK DATA ANALYTICS FUNCTIONS (NWDAF)

NWDAF play a pivotal role in enhancing the performance and efficiency of core network environments by using AI and ML techniques to collect, analyse, and interpret network data, enabling operators to make informed decisions to optimise network operations. Key functions include:

- **Traffic analysis and optimisation**: Real-time analysis of traffic patterns enables dynamic load balancing and efficient resource allocation for better QoS.
- **Predictive analytics**: ML models predict network issues like congestion or failures, allowing for preventive actions, especially in non-terrestrial networks with variable conditions.
- **Network performance monitoring**: Continuous monitoring helps optimise the core network, improving efficiency and reducing downtime.

Nokia introduced its commercial NWDAF in early 2022, leveraging AI and ML to enable applications to access network data via a consume/publish model[17]. This solution targets fast-response applications for connected devices, offering benefits such as improved QoE, IoT security, and network optimisation. It is available both on-premises and as a cloud-native, consumption-based service on Google Cloud.

3.2.2 GENERATIVE AI

Generative AI (GenAI) in telecommunications refers to the use of advanced ML models, particularly Large Language Models (LLMs) and multimodal systems, to generate insights, automate processes, and optimise network operations. These AI models go beyond traditional analytics by providing context-aware responses, predictions, and solutions.

The use of LLMs in telecommunications is rapidly expanding. Initially developed for natural language processing, LLMs now play a key role in tasks such as network optimisation, traffic prediction, and troubleshooting[18]. By learning from historical network data, LLMs can forecast traffic loads, helping to optimise resources and prevent congestion – a critical capability as 5G and IoT networks generate increasing volumes of data. LLMs also assist in troubleshooting by analysing network logs to identify problems and suggest solutions, while automating tasks, including configuration and load balancing. Despite their potential, challenges such as high computational costs remain, especially at the network edge, prompting the use of Parameter-Efficient Fine-Tuning (PEFT)[19] techniques, such as Quantized Low-Rank Adaptation (QLoRA)[20], and split edge learning (distributed learning).

Another GenAI application is alignment via RAG[18]: GenAI supports alignment in terrestrial and non-terrestrial networks by leveraging Retrieval-Augmented Generation (RAG) to access dynamic databases containing up-to-date 3GPP standards and regulatory guidelines. This ensures telecommunication models remain compliant with evolving requirements, while optimising wireless system performance. By integrating reinforcement learning with wireless feedback, GenAI models can adapt their responses to QoE for network agents, enabling smarter, regulation-aware network management.

Datasets play a crucial role in GenAI, serving as essential resources for training, fine-tuning for specialised tasks, and evaluating models for telecommunication applications. They enable these models to recognise patterns, generate accurate predictions, and optimise various aspects of network management and operations. Examples of telecommunication datasets include TeleQnA[21], TSpec-LLM[22], Tele-llms[23], Spec5G[24], and Oran-bench-13k[25].

3.2.3 FEDERATED LEARNING

FL has emerged as a transformative approach in AI[26], enabling collaborative model training without sharing raw data across devices or networks. The implementation of FL in core networks addresses critical challenges related to data privacy, latency, and scalability. Integrating FL into these networks allows for distributed AI model training directly at edge devices or local nodes, minimising data transfer and enhancing security. By leveraging the hierarchical architecture of core networks, FL ensures that models are updated locally and aggregated securely at the core, preserving user privacy while optimising resource efficiency.

This decentralised approach also supports latency-sensitive applications, such as autonomous systems, remote healthcare, and next-generation IoT, by reducing the reliance on centralised data processing. FL aligns seamlessly with terrestrial and non-terrestrial networks' goals of low latency, high reliability, and robust security, making it an essential component in the evolution of intelligent, interconnected systems.

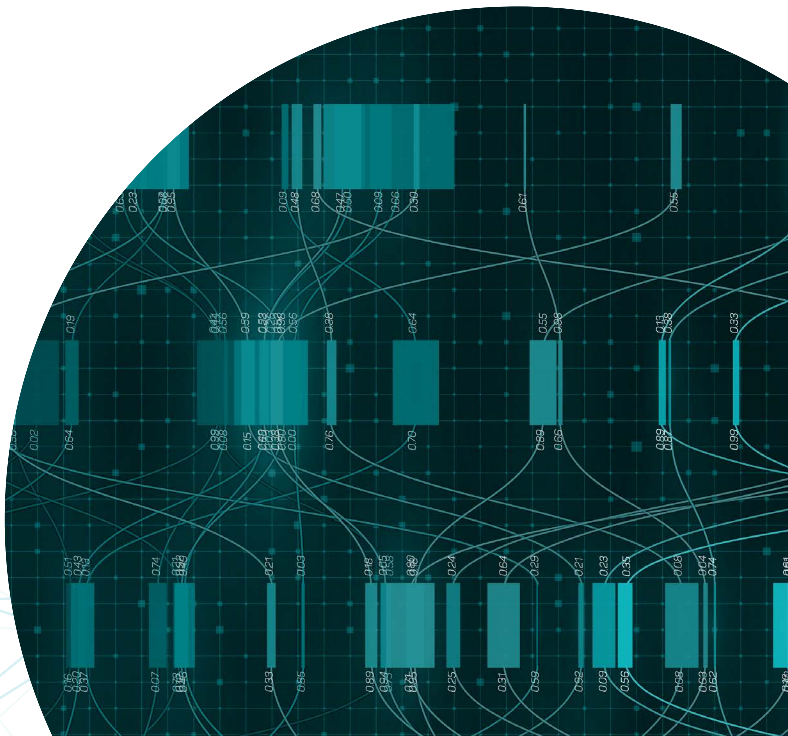
Recent research by Ericsson demonstrated how FL can be seamlessly integrated into the 3GPP 5G NWDAF architecture[27]. The study introduced a Multi-Party Computation (MPC) protocol to protect the confidentiality of local model updates during aggregation. Such advancements address the critical concern of end-user privacy and enhance the practical deployment of FL in real-world 5G networks.

Fine-tuning LLMs traditionally requires vast amounts of labelled data and centralised training, which poses challenges related to privacy, data ownership, and computational costs. Hence, FL offers a decentralised alternative, allowing multiple clients to train a global model collaboratively while keeping data local. This preserves privacy and mitigates risks associated with centralised data aggregation.

However, standard FL approaches optimise for a single global model, which may not generalise well across diverse datasets and tasks. To address this, Federated Multi-Task Learning (FMTL)[28] extends FL by enabling clients to train personalised models, while still benefiting from shared knowledge. By representing clients as nodes in a graph and modelling task similarities as edges, FMTL helps develop models that are both specialised and informed by related tasks.

3.3 END-TO-END AI-DRIVEN NETWORK OPTIMISATION

End-to-End (E2E) AI-driven network optimisation refers to the comprehensive application of AI and ML models throughout the entire lifecycle of a telecommunication network – from planning and design, to real-time management and optimisation. These solutions leverage AI techniques to automate processes, optimise resource allocation, and improve the QoS across the network's various segments.



3.3.1 KEY COMPONENTS

AI-based network optimisation spans several layers, including network planning, real-time operation, anomaly detection, traffic management, and fault management. Below are the main components that facilitate an intelligent, self-optimising network.

Key components of AI-driven optimisation	Description
Network Planning & Design Optimisation	AI models are used to optimise the network design by analysing demand projections, geographical data, and traffic patterns, ensuring that both TN and NTN infrastructures are scalable and efficient.
Traffic Forecasting & Load Balancing Across Layers	AI forecasts traffic demand and adjusts traffic load distribution across multiple network layers (access, transport, core, and NTN), ensuring optimal performance at all levels.
Real-Time Resource Allocation & Scheduling	AI enables real-time allocation of network resources (e.g., bandwidth, spectrum, compute power) across all network segments, minimising congestion, balancing loads, and enhancing service quality.
E2E Fault Management & Self-Healing	AI-driven solutions identify and mitigate network faults across the entire system, from edge to core and NTN. AI models proactively reconfigure paths, reroute traffic, and restore service autonomously.
Holistic QoS Optimisation	E2E optimisation ensures that all layers are fine-tuned to provide consistent QoS, adjusting latency, bandwidth, and throughput dynamically across terrestrial and satellite-based components.
Multi-Layer Anomaly Detection & Security	AI continuously monitors the entire network for anomalies, from the edge devices through the core to NTN. It can detect and mitigate security threats, network congestion, or faults across all network segments.
Integrated Spectrum & Radio Resource Management	AI optimises spectrum usage and resource allocation across both terrestrial and NTN networks, ensuring seamless integration and minimising interference between network layers.

3.3.2 AI TECHNOLOGIES DRIVING NETWORK OPTIMISATION

The following AI techniques play a crucial role in the E2E optimisation of terrestrial and non-terrestrial networks:

AI Technologies	Description
ML & Deep Learning (DL)	These AI techniques are used across the entire network lifecycle to predict, optimise, and manage resources in real time and during network planning. ML/DL models are trained to handle diverse data inputs from both TN and NTN.
Edge Computing with AI	AI at the edge of the network ensures that data processing is distributed efficiently, reducing latency and enabling real-time decision-making for E2E optimisation.
Predictive Analytics	AI-driven predictive analytics enables proactive management, anticipating issues (like congestion or failure) across all layers, from core to edge, in both terrestrial and satellite networks.
Reinforcement Learning (RL)	RL is applied to dynamically optimise E2E processes like routing, load balancing, and spectrum allocation based on rewards and penalties, adapting as conditions change in the network.
Graph Neural Networks (GNNs)	GNNs model complex relationships across network topologies (e.g., inter-layer communication in TN and NTN), allowing for optimal routing, load balancing, and decision-making in large, multi-layered networks.

3.3.3 CHALLENGES IN IMPLEMENTING E2E OPTIMISATION

Implementing E2E AI-driven network optimisation in TN/NTN presents several challenges. One of the main difficulties is **integrating AI across multiple network layers**, such as the core, access, edge, and NTN. Each layer has unique systems and protocols, making seamless coordination complex. Additionally, data is often restricted within specific network layers, making it challenging for AI to get a full view of the entire network for optimisation.

Real-time processing also becomes a challenge, as AI must handle large data volumes and make quick decisions without introducing latency. This is particularly difficult in NTN where satellite communication can introduce delays. Another obstacle is ensuring that AI systems are **compatible across different technologies** like 5G and satellite-based systems, which have varying requirements (latency, bandwidth, computational resources, etc.).

Security and privacy concerns are heightened when AI uses large amounts of network data, and there's always the risk of attacks targeting AI models. Finally, **scalability** is a challenge as the network grows, and AI systems must adapt to increasing traffic and new technologies, which requires continuous **model retraining** and adjustments.

3.4 AI IN DEVICES

AI's integration into end-user devices enhances functionality, user experience, and connectivity. Examples include:

- **Mobile phones**: AI powers personalised applications, advanced speech recognition, real-time language translation, and adaptive battery optimisation. It also enhances connectivity settings by analysing network conditions.
- **Laptops and PCs**: AI-driven tools improve productivity with intelligent task scheduling, enable seamless video conferencing with noise suppression and background adjustments, and enhance security with behavioural-based threat detection.
- **Connected vehicles**: AI supports autonomous driving by processing sensor data for navigation, traffic analysis, and Vehicle-To-Everything (V2X) communication. It ensures safety and efficient vehicular operations by anticipating road conditions and optimising energy usage.
- **Home Customer Premises Equipment (CPE)**: AI in routers and modems dynamically adjusts Wi-Fi coverage, proactively resolves connectivity issues, and secures home networks by detecting and mitigating cyber threats.
- **Satellite, Drones and High-Altitude Platforms (HAPs):** AI optimises satellite communication, adjusts orbital paths, and mitigates interference. Devices in NTNs can autonomously manage their operations, adapting to environmental conditions such as weather or signal interference, for more reliable and efficient communication.

3.5 AI IN INDUSTRY APPLICATIONS

The growing need for real-time data processing, autonomous decision-making, and optimised network operations is creating a unique synergy between AI and the devices within the networks. AI is not only enabling smart devices but also empowering TN and NTN infrastructures to adapt, evolve, and deliver highly reliable connectivity on a global scale.

AI's transformative potential extends to enabling E2E applications across various industries:

- **Aviation**: AI optimises flight paths, enhances safety with real-time air traffic monitoring, and ensures predictive maintenance for aircraft systems, reducing delays and improving operational efficiency.
- **Maritime**: AI supports autonomous navigation, real-time weather analysis, cargo optimisation, and predictive maintenance of critical systems, improving safety and efficiency in global shipping operations.
- **Media and entertainment**: AI revolutionises content delivery through adaptive streaming, personalised recommendations, and automated editing. It also enables real-time language translation and captioning for global audiences to enhance accessibility.
- **Healthcare**: AI facilitates remote diagnostics and real-time patient monitoring through wearables. It automates personalised treatment planning and employs predictive tools for early intervention, streamlining healthcare services and improving patient outcomes.
- **Logistics and supply chain**: AI optimises route planning, warehouse management, and inventory tracking. By leveraging predictive analytics, it enhances delivery performance and minimises disruptions, ensuring seamless supply chain operations.
- **Energy and sustainability**: AI plays a key role in optimising energy consumption, improving grid management, and supporting sustainable practices. AI systems can predict energy demand, optimise renewable energy usage, and enhance the efficiency of power plants. In addition, AI helps monitor environmental conditions, track emissions, and suggest energy-saving strategies, contributing to greener, more sustainable industrial operations.

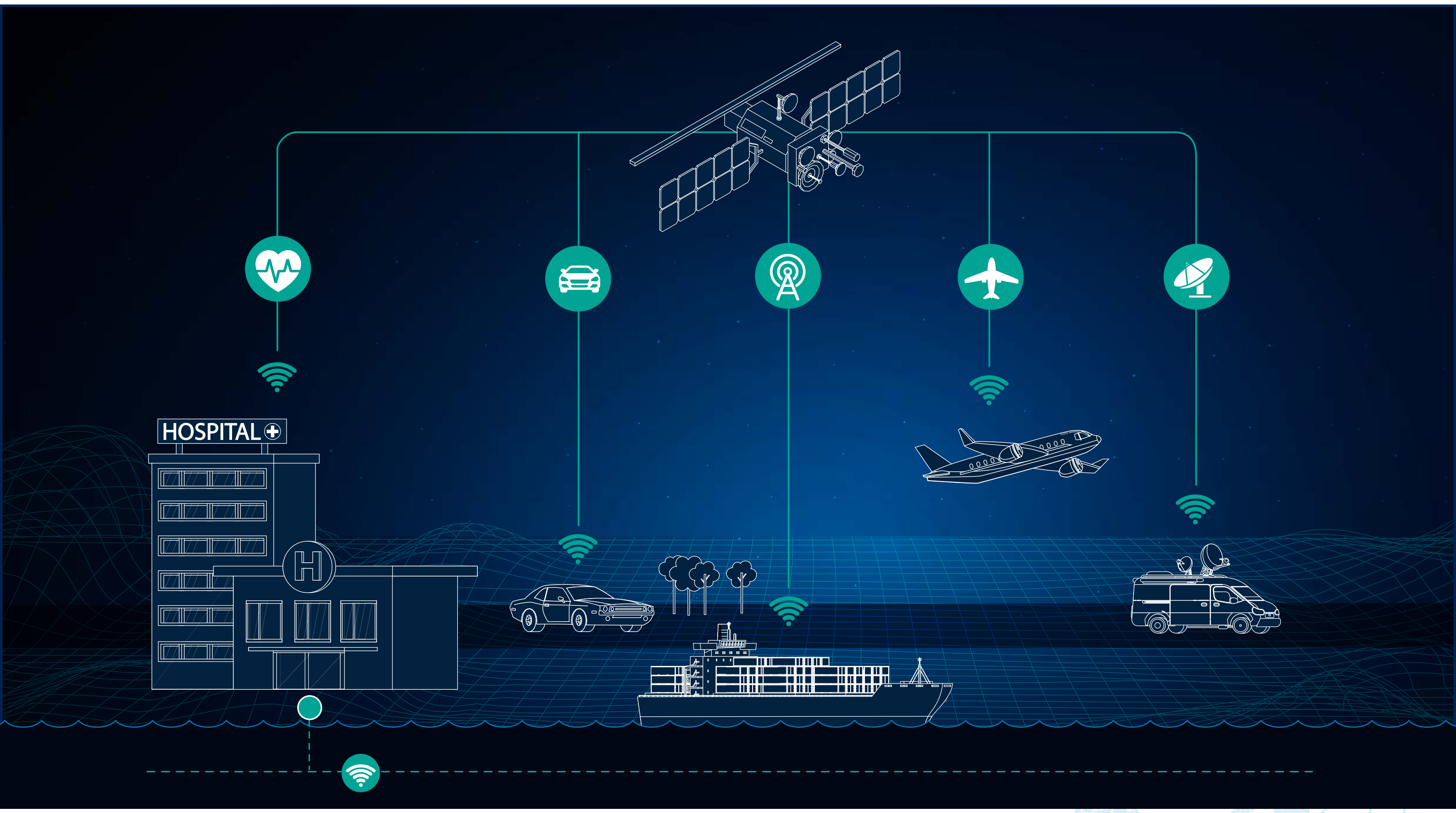


Fig. 2: *AI-enabled global connectivity across terrestrial and non-terrestrial networks.*

4. THE EVOLUTION OF AI IN 3GPP STANDARDISATION

The role of standardisation is crucial for the development, interoperability, and global adoption of technologies in telecommunications. In the rapidly evolving field of 5G, NTN, and AI-driven services, standardised protocols ensure seamless integration and compatibility across different devices, networks, and services. The 3GPP has been instrumental in standardisation by:

- **Defining AI/ML use cases**: Starting with Release 15, the 3GPP introduced Network Data Analytics Function (NWDAF), enabling advanced analytics for resource optimisation, anomaly detection, and enhanced mobility management. Release 16 expanded AI's role to include network slice management and energy efficiency mechanisms, while Release 17 incorporated AI-driven enhancements in QoS prediction and traffic steering, further supporting NTN integration.
- **Standardising interfaces for AI integration**: Unified frameworks for AI-enabled interfaces were solidified in Release 16, providing standardised communication protocols between network components and AI-driven functions. This ensures interoperability and accelerates the deployment of AI solutions across TNs and NTNs.
- **Enabling Open RAN collaboration**: Open RAN standards in 3GPP foster multi-vendor AI solutions. Through Release 18, Open RAN interfaces now support real-time AI-driven beamforming and RAN energy savings, facilitating innovation and cost efficiency across diverse ecosystems.
- **Advancing federated learning**: Releases 17 and 18 introduced frameworks for federated learning, allowing collaborative training of AI models, while preserving data privacy. These methods enhance the development of robust AI systems tailored to dynamic network environments.

Release 19 of 3GPP is still in progress and focuses on advancing the capabilities of 5G and preparing for future technologies, including 6G. It is expected to build upon the innovations introduced in Release 17 and Release 18, with a focus on enhancing network efficiency, AI-driven operations, edge computing, and integrating NTNs.

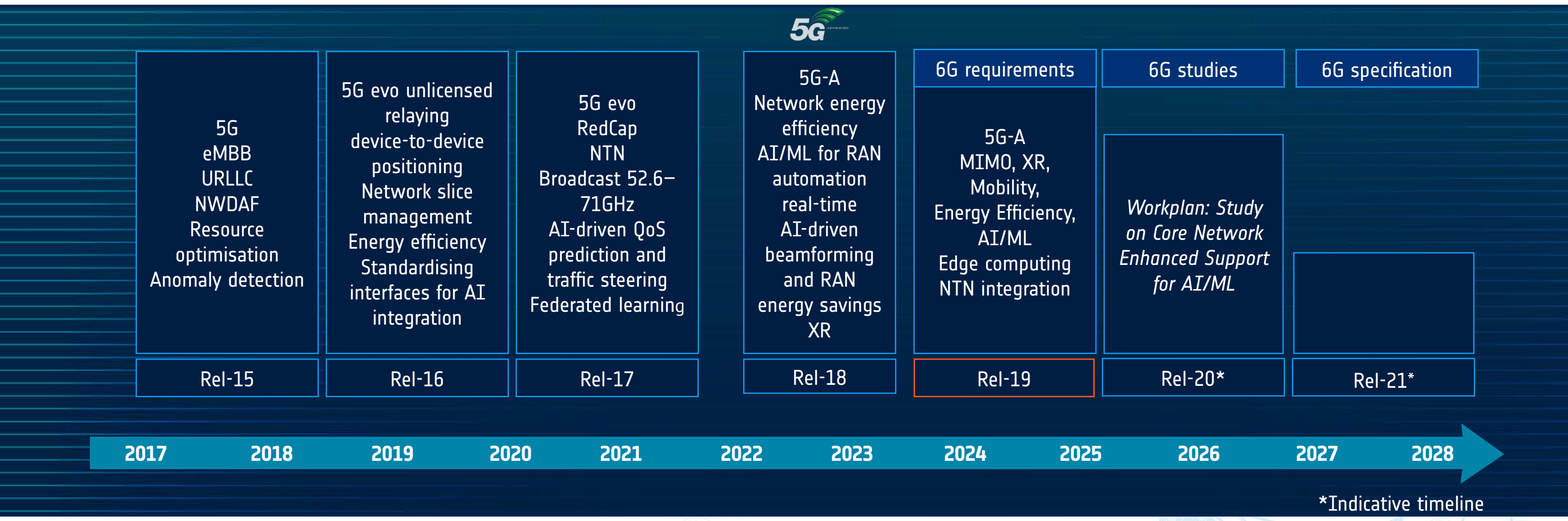


Fig. 3: *The evolution of AI in 3GPP standardisation – based on Ericsson's view of the 5G Advanced and 6G timeline of 3GPP*[29].

5. CHALLENGES AND MITIGATIONS

The integration of AI-driven connectivity solutions in TN and NTN presents numerous opportunities to enhance network performance, optimise resource allocation, and drive innovation. However, it also introduces a range of challenges that must be addressed to ensure the responsible deployment of these technologies. These challenges span across technical, regulatory, security, and operational domains, with particular emphasis on ensuring that AI systems are fair, transparent and accountable.

As AI becomes more integral to network management and service delivery, it is critical to address concerns around data privacy, security risks, and ensuring trustworthy, explainable, and ethical AI deployment. Tackling these challenges will be essential for building trust among stakeholders and promoting the widespread adoption of AI technologies in TN/NTN.

5.1 DATA PRIVACY AND SECURITY

AI models, especially those deployed in telecom networks, rely on large datasets for training to enable effective decision-making and optimisation. Nevertheless, collecting and processing such data raises significant privacy concerns, regulatory constraints, and cybersecurity risks. In the context of NTNs, which involve complex infrastructures such as satellites and UAS, these challenges are amplified. The distributed nature of NTN systems, which may involve multiple geographic locations and varying data sources, increases the risk of data breaches and unauthorised access. Additionally, maintaining compliance with regional data privacy laws (such as GDPR in Europe) becomes more complicated when data is spread across different jurisdictions.

To address these concerns, federated learning offers a promising solution, by enabling AI training without centralised data storage, preserving privacy and complying with regulations that restrict data sharing. The aggregation of model updates (rather than raw data) at a central server ensures that no private information is transferred, while still enabling collective learning.

Moreover, additional techniques such as homomorphic encryption[30] and differential privacy[31] can be integrated into the FL framework to further enhance data security. These methods allow computations to be performed on encrypted data, ensuring that sensitive information is never exposed during the training process.

5.2 AI-DRIVEN ATTACKS ON WIRELESS NETWORKS

AI can significantly enhance wireless network performance and security, but it also introduces new threats. Malicious actors can leverage AI to launch sophisticated attacks, such as intelligent jamming, spoofing, and eavesdropping, by learning from network data and adjusting their tactics in real time. AI-powered techniques, like Generative Adversarial Networks (GANs) and deep fakes, can generate fake signals or impersonate legitimate users, leading to data breaches or network disruptions. Additionally, AI can enable attackers to coordinate and synchronise their actions, while adapting and evolving their strategies in response to network security countermeasures, by utilising multi-agent systems, game theory, or genetic algorithms[32].

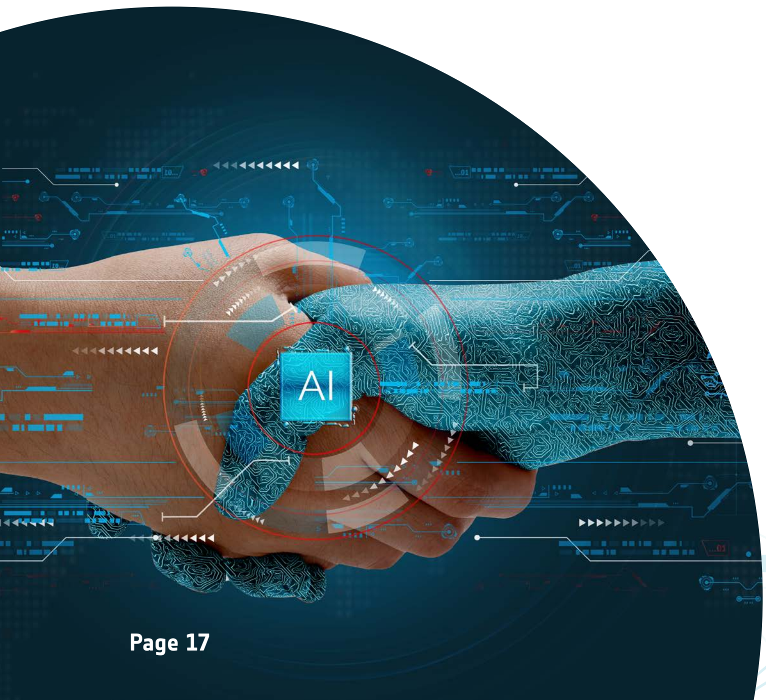
To mitigate these risks, AI-driven defence mechanisms can be used to detect and counteract attacks by identifying abnormal network patterns and using ML for real-time threat detection. Encryption and authentication systems enhanced with AI can prevent breaches, while anomaly detection tools utilising reinforcement learning can identify evolving attack strategies.

Additionally, deception techniques can mislead attackers, preventing successful exploitation. By leveraging AI for both defence and detection, network operators can strengthen their defences against AI-driven cyberattacks while improving overall security.

5.3 TRUSTWORTHY, EXPLAINABLE AND ETHICAL AI DEPLOYMENT

AI models often function as complex black boxes, making it challenging for network operators to interpret decisions, diagnose failures, or ensure compliance with regulations. Moreover, due to the vast amounts of data used for training, development processes must ensure that models learn only the intended patterns and behaviours without introducing unintended biases or inaccuracies. This is especially critical in telecommunication applications, where decisions made by AI can directly impact user experience, privacy, and system reliability.

It is also essential to have a clear and transparent understanding of how these models operate, which can be achieved through Explainable AI (XAI) techniques that provide insights into the decision-making process, enabling stakeholders to better trust the AI's actions. Ultimately, maintaining trust in the overall system depends on ensuring that AI is both reliable and ethical, functioning as expected without introducing physical, financial, or ethical risks, and ensuring its decisions are aligned with societal values[33].



5.4 STANDARDISATION AND INTEROPERABILITY

Global standards are needed to ensure seamless integration, compatibility, and cooperation across multi-vendor ecosystems, fostering innovation and cost efficiency. Interoperability plays a crucial role in enabling AI-driven telecom networks to function across different infrastructures, devices, and service providers, ensuring consistent performance and scalability. In TN and NTN environments – where networks must operate across terrestrial, satellite, and airborne platforms – interoperability is essential for maintaining seamless connectivity and data exchange.

Governments, companies, and standards bodies worldwide are recognising the need for trustworthy and interoperable AI systems and are establishing regulations to address this. Examples of such initiatives are the European Union AI Act[34], which is the first-ever comprehensive legal framework on AI worldwide, aiming to foster trustworthy AI in Europe, and the UK Government's white paper on AI regulation[35]. These regulatory efforts seek to create frameworks that enable safe and ethical AI deployment while ensuring consistency across different markets and regions.

Another initiative is AI for Good Global Summit[36], organised by the ITU in partnership with 38 United Nations (UN) sister agencies and co-convened with Switzerland, which focuses on identifying trustworthy AI applications that support the 17 UN Sustainable Development Goals (SDGs). Targeted for achievement by 2030, it aims to build skills, set standards, and advance AI governance for sustainable development.

Interoperability frameworks and open standards are vital for ensuring AI models, data formats, and operational protocols can seamlessly interact across different networks and vendors. Initiatives such as 3GPP's AI/ML standardisation efforts and industry-driven projects like the O-RAN Alliance are crucial for promoting open, interoperable, and secure AI-powered telecom networks.

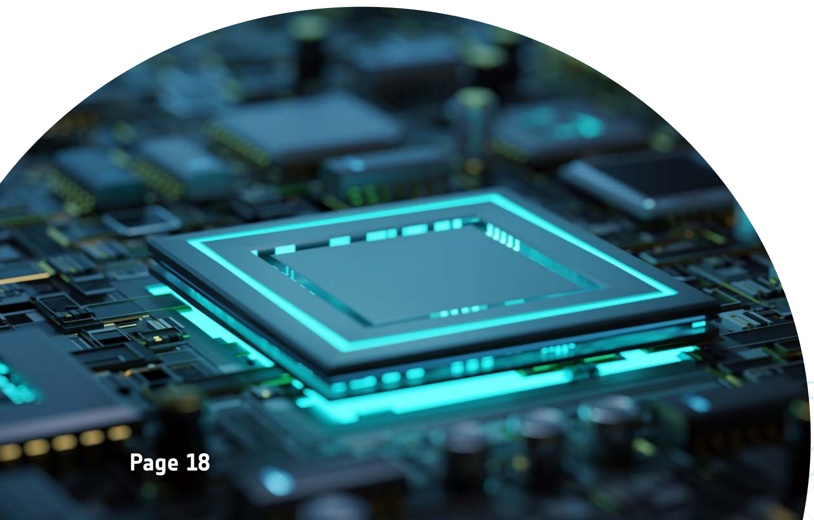
6. THE FUTURE OF AI IN NETWORKS

As AI continues to evolve, its role in telecommunications networks is expected to grow exponentially. Future AI-driven networks will not only optimise performance but also enable self-learning, autonomous, and highly adaptive communication systems capable of handling the increasing complexity of next-generation connectivity.

6.1 HARDWARE SOLUTIONS

The future of AI-driven networks relies not only on software advancements but also on innovative hardware solutions that enhance computational efficiency, speed, and energy consumption. Emerging technologies such as neuromorphic computing, quantum advancements, and AI-optimised chips are set to revolutionise AI processing in telecommunications, edge computing, and NTN systems.

- **Neuromorphic computing**: replicates brain-like processing using Spiking Neural Networks (SNNs) and specialised chips for low-power, real-time AI inference, ideal for edge AI and low-latency TN and NTN applications. Key benefits include ultra-low power consumption for satellites and IoT, real-time adaptability to dynamic network conditions, and event-driven processing for efficient data transmission. Companies like Intel (Loihi), IBM (TrueNorth), and BrainChip (Akida) are advancing neuromorphic chips to enhance AI-driven decision-making at the network edge.



- **Quantum computing** has the potential to revolutionise AI in telecommunications by solving complex network optimisation problems exponentially faster. Unlike classical computers, which process data in binary, quantum computers leverage qubits to perform multiple calculations simultaneously through superposition and entanglement. This advancement enables faster network optimisation, allowing real-time traffic and resource management. Quantum cryptography, particularly Quantum Key Distribution (QKD), enhances security by making AI-driven networks resistant to cyber threats and eavesdropping. Additionally, quantum computing accelerates AI training by enabling federated learning models to process vast datasets in parallel, significantly reducing training times for AI models in 6G and beyond. While still in development, companies such as Google, IBM, and D-Wave are actively working on quantum AI applications, which could be integrated into future telecommunication infrastructures.

- **Specialised Application-Specific Integrated Circuits (ASICs)**: ASICs designed for AI tasks enhance performance and energy efficiency across TN/NTN, reducing operational costs and improving sustainability. ASICs reduce operational costs and contribute to sustainable AI deployment in telecom networks, making them ideal for edge AI, real-time data processing, and autonomous network management in 6G and NTN ecosystems. In the context of AI, ASICs have already been deployed in several commercially available products, such as Google's Tensor Processing Units (TPUs), specifically designed for AI and ML tasks, and Tesla's Dojo chip, designed for deep learning in autonomous driving.

- **CubeSats**: small, cost-effective satellites ideal for AI-driven applications in NTN. By incorporating AI processors and algorithms, CubeSats can autonomously collect, process, and analyse data at the edge, enabling real-time decision-making and low-latency communication in remote or underserved areas. With AI-enhanced capabilities, CubeSats can improve resource allocation, monitor network health, and optimise traffic routing. This makes satellites a vital component of future AI-driven networks, especially in environments where terrestrial infrastructure is sparse or non-existent. Their integration with AI will enable them to support global connectivity, disaster recovery, and space-based communication, bringing new opportunities for AI at the edge. The survey conducted by N. Saeed et al.[37] describes all the potential future applications of Cubesats for satellite communications.

6.2 AI FOR THE CYBER-PHYSICAL WORLD

As AI continues to evolve, its role in the cyber-physical world will be transformative, enabling seamless interaction between digital and physical systems. AI-driven models will bridge the gap between virtual simulations and real-world infrastructure, enhancing network efficiency, reliability, and security.

AI-driven digital twins will redefine network management by creating real-time, virtual replicas of physical network elements, including base stations, satellites, fibre-optic links, and IoT devices. These models will allow operators to analyse system behaviour, predict failures, and proactively optimise network performance.

Physics-aware AI will integrate wireless communication principles such as electromagnetic wave propagation, beamforming, and interference modelling to enhance signal transmission and spectrum efficiency. AI-driven physics models will be key to overcoming the challenges of Millimetre-Wave (mmWave) and Terahertz (THz) frequencies, where precise beamforming and dynamic power adjustments are essential.

6.3 AI-NATIVE 6G

The future of telecommunication is set to be transformed by the convergence of AI and 6G, where AI will be deeply embedded into the core of network architecture. Unlike previous generations of mobile networks, 6G will be AI-native, meaning AI will not just be an add-on but a fundamental part of its design from the very beginning. According to Nokia[38], 6G will not work without AI, as AI will drive system design, optimisation, and automation across RAN, cloud infrastructure, and network management. This integration will redefine how telecom networks are built, operated, and monetised, enabling unprecedented levels of efficiency, adaptability, and intelligence.

The European Space Agency (ESA) is already taking steps toward AI-driven 6G NTN with its 6G Satellite Precursor initiative[39]. This programme explores the role of AI in optimising satellite-based 6G connectivity, ensuring seamless integration between terrestrial and non-terrestrial networks. AI-driven satellites will enhance coverage, reduce latency, and dynamically allocate resources based on demand, making AI-powered NTN essential for global 6G deployment. The initiative reflects the growing recognition that satellite networks will be a critical component of 6G, particularly for remote and underserved areas where terrestrial infrastructure is limited.

As we move toward this AI-native era, collaboration between industry leaders, policymakers, and researchers will be essential to unlocking the full potential of AI in telecoms. The future of connectivity will not only be faster and more intelligent but also more inclusive and sustainable, bridging the digital divide and redefining how the world stays connected.

7. CONCLUSION AND CALL TO ACTION

AI's role extends beyond operational improvements; it also underpins the innovation required for future telecommunications advancements. By automating complex operations, enabling scalability, optimising resources, and enhancing reliability, AI ensures networks are equipped to meet the demands of emerging applications such as Augmented Reality (AR), Virtual Reality (VR), autonomous systems, and smart cities. The convergence of AI with 6G and beyond will drive transformative changes, bringing the vision of ubiquitous, intelligent, and sustainable connectivity closer to reality.

AI-driven terrestrial and non-terrestrial networks are set to transform global connectivity, aligning with ESA's mission to foster innovation, sustainability, and inclusivity. However, alongside these advancements come significant challenges, including data privacy, security risks, ethical considerations, and interoperability concerns. This white paper serves as a call to action for stakeholders across the telecommunications ecosystem to drive research, establish best practices, and develop AI-native solutions that ensure secure, efficient, and sustainable connectivity for the future. ESA invites industry leaders, researchers, and policymakers to collaborate in shaping the next generation of networks that redefine connectivity for industry and society.

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