सत्यमेव जयते

Study Paper
On
OPPORTUNITIES FOR ARTIFICIAL INTELLIGENCE IN COMMUNICATION NETWORKS

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Abstract

The enormous growth in data traffic in communication networks, combined with increasingly intricate network designs, presents formidable challenges for efficient resource allocation and optimization. In recent years, Artificial Intelligence (AI) has emerged as a transformative force in the telecommunication industry, revolutionizing various aspects of network management and performance enhancement. This paper provides an in-depth analysis of AI's potential applications in communication networks, focusing on areas such as resource allocation, network optimization, fault detection, security improvement, customer experience enhancement, predictive maintenance, and fraud detection. Several AI approaches, including evolutionary algorithms, deep learning, reinforcement learning, and machine learning, are explored in their application to communication network management. Additionally, the study discusses the current status of research, challenges faced, and potential avenues for leveraging AI to enhance network performance, reliability, and security. Through real-world examples and emerging trends, this paper highlights AI's role in shaping the future of telecommunications by enabling faster, more efficient, and smarter communication networks.

1.0 Introduction

AI has been one of the most transformative technologies of the past few decades, revolutionizing industries such as healthcare and finance. Its impact on communications and the information society has been particularly significant. As communication is deeply intertwined with information exchange, it forms a key element of modern society [1]. The telecommunications industry plays a critical role in connecting people, businesses, and devices across the globe. As technology continues to advance at an unprecedented pace, the integration of Artificial Intelligence (AI) in telecommunications has emerged as a transformative force.

The telecom industry is undergoing significant transformation due to technological advancements, including increased data volume, enhanced computational power, and sophisticated computing architectures. While sectors like retail, finance, healthcare, and transportation have rapidly adopted AI to redefine their operations, telecom operators have been relatively slower to embrace these changes. However, this is changing rapidly. Telecom operators are now recognizing AI's immense potential and are beginning to harness its transformative capabilities. AI is revolutionizing the way telecom operators deliver services, enhance customer experience, optimize network management, and drive operational efficiencies. By leveraging AI, telecom companies can unlock new possibilities, revolutionize operations, and provide customers with personalized experiences.

AI is being used to improve network performance, automate customer service tasks, and personalize user experiences. As a result, telecommunications companies can deliver better services to their customers and stay ahead of the competition. AI's remarkable capability to process vast amounts of data, recognize patterns, and autonomously make intelligent decisions makes it a powerful tool for transforming communication networks. AI-powered solutions can optimize network operations and resource allocation, predict and mitigate security threats, and offer numerous benefits to enhance the performance and resilience of modern communication infrastructures.

The convergence of 5G (Fifth Generation) networks, the Internet of Things (IoT), and the growing volume of Big Data has propelled Communications Service Providers (CSPs) to focus on AI. Advanced algorithms, Machine Learning (ML), and Deep Neural Networks (DNNs) enable AI technologies to analyze vast datasets, identify patterns, and make intelligent predictions. This report provides an overview of the use of AI in telecommunications, highlighting its impact, applications, challenges, and future directions in shaping the next generation of communication networks [2].

2.0 Overview of AI

AI has been defined differently over time. Modern AI is the intelligence demonstrated by machines, distinct from the natural intelligence displayed by humans or animals. AI involves studying intelligent agents—systems that perceive their environment and take action to achieve their goals [3].

Recent advancements in AI have driven innovations in fields such as natural language processing, computer vision, robotics, gaming, and decision-making systems. The ongoing evolution of AI has the potential to enhance human capabilities, revolutionize industries, and tackle complex challenges across various domains, including healthcare, scientific research, transportation, and sustainable energy solutions.

Integrating AI methods into communication networks can address complex challenges and capitalize on new opportunities. The combination of traditional AI and Generative AI (GenAI) will offer the industry a unique opportunity to rethink and reinvent traditional business and operating models.

Key AI methodologies for optimizing network operations and performance include:

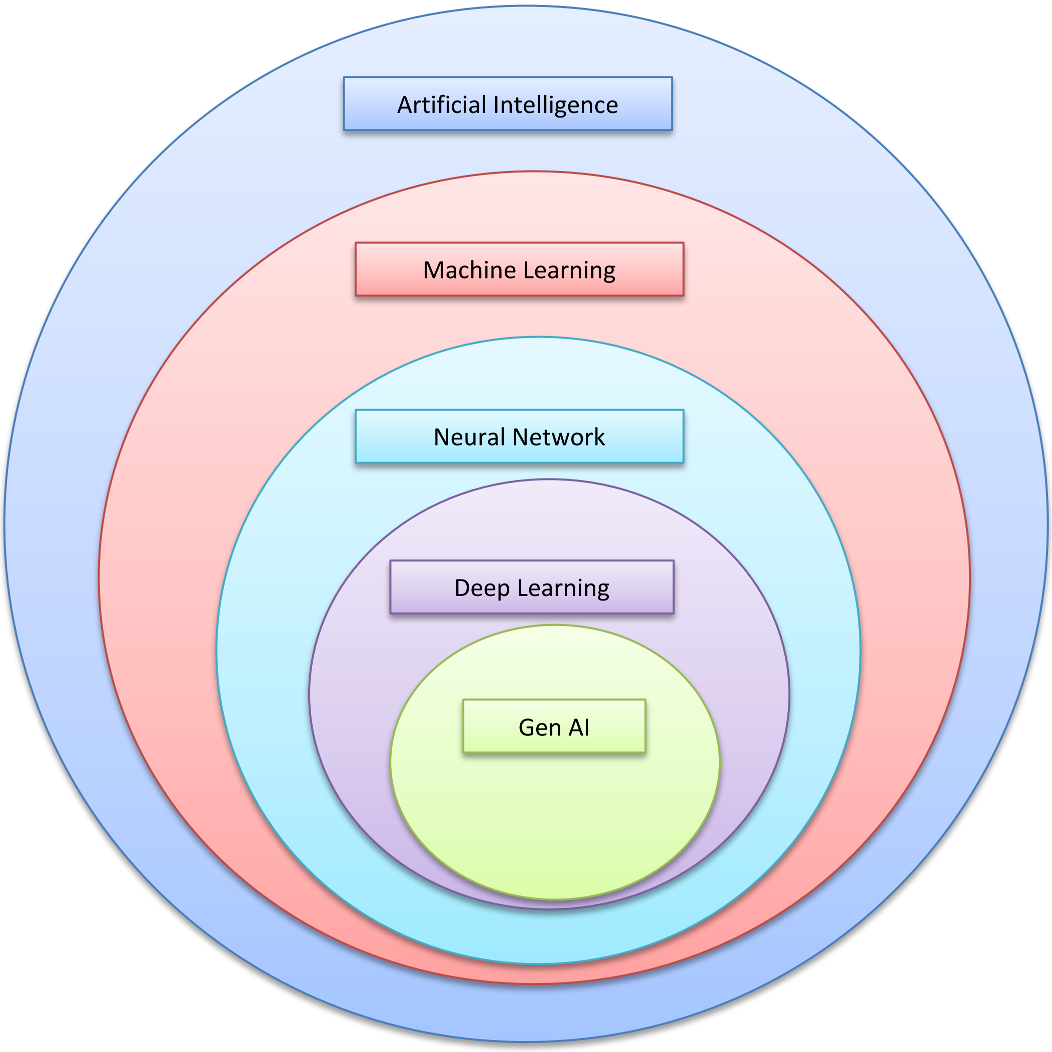

Figure 1 The relationship between AI, Machine Learning, Neural Network, Deep Learning, and Generative AI

Artificial Intelligence (AI):

Artificial Intelligence (AI) refers to the development of computer systems of performing tasks that require human intelligence. AI aids, in processing amounts of data identifying patterns and making decisions based on the collected information. This can be achieved through techniques like Machine Learning, Natural Language Processing, Computer Vision and Robotics. AI encompasses a range of abilities including learning, reasoning, perception, problem solving, data analysis and language comprehension. The ultimate goal of AI is to create machines that can emulate capabilities and carry out diverse tasks, with enhanced efficiency and precision.

Machine Learning (ML):

Machine learning is a branch of artificial intelligence that enables algorithms to uncover hidden patterns within datasets. It allows them to predict new, similar data without explicit programming for each task. Machine learning finds applications in diverse fields such as image and speech recognition, natural language processing, recommendation systems, fraud detection, portfolio optimization, and automating tasks. Machine learning's impact extends to autonomous vehicles, drones, and robots, enhancing their adaptability in dynamic environments. In communication networks, ML techniques are used for tasks such as traffic prediction, anomaly detection, and resource optimization. ML models, trained on historical network data, can forecast future traffic demands, enabling proactive network management and capacity planning. Furthermore, ML-based anomaly detection algorithms can identify abnormal network behavior, indicating security breaches or performance degradation, thus facilitating timely mitigation actions.

Neural Network:

A neural network is a machine learning program, or model, that makes decisions in a manner similar to the human brain, by using processes that mimic the way biological neurons work together to identify phenomena, weigh options and arrive at conclusions. Every neural network consists of layers of nodes, or artificial neurons—an input layer, one or more hidden layers, and an output layer. Each node connects to others, and has its own associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network. Neural networks rely on training data to learn and improve their accuracy over time. Once they are fine-tuned for accuracy, they are powerful tools in computer science and artificial intelligence, allowing us to classify and cluster data at a high velocity. Tasks in speech recognition or image recognition can take minutes versus hours when compared to the manual identification by human experts. One of the best-known examples of a neural network is Google's search algorithm. Neural networks are sometimes called artificial neural networks (ANNs) or simulated neural networks (SNNs). They are a subset of machine learning, and at the heart of deep learning models.

Deep Learning (DL):

Deep learning is a subset of machine learning that utilizes multilayered neural networks, known as deep neural networks, to simulate the complex decision-making processes of the human brain. Unlike traditional machine learning models that use simple neural networks with one or two layers, deep learning models employ three or more layers, often hundreds or thousands, to train the models. It is used in communication networks for traffic classification, QoS (Quality of Service)/QoE (Quality of Experience) enhancement, and network security. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) effectively analyze network traffic patterns and distinguish between different application types. DL models support dynamic QoS provisioning and adaptive network management based on real-time traffic attributes.

Generative AI:

Generative AI, often referred to as GenAI, is a subset of artificial intelligence that can create original content such as text, images, videos, audio, or software code in response to user prompts. This technology relies on sophisticated machine learning models, particularly deep learning models, which simulate the learning and decision-making processes of the human brain.

3.0 AI in Communication Networks

Integrating AI in communication networks presents trans-formative opportunities for enhancing network efficiency, reliability, and user experience. By leveraging AI technologies, communication networks can be optimized to handle increasing data traffic, provide robust security measures, and offer personalized services. Below are key areas where AI can significantly impact communication networks [4]:

3.1. AI in Satellite Communication

Satellite communication holds the potential to provide continuous service in under-served or remote areas, offering global connectivity, service ubiquity, and scalability. However, to fully realize these advantages, significant challenges in resource management, network control, security, spectrum utilization, and energy efficiency must be addressed, as satellite networks face more stringent constraints than terrestrial systems. Artificial Intelligence (AI) – encompassing machine learning, deep learning, and reinforcement learning – has shown great promise in addressing these challenges. AI has already proven its value across various fields, including wireless communication, and its application to satellite networks reveals significant potential.

This section offers an extensive overview of AI and its diverse sub-fields, highlighting state-of-the-art algorithms tailored to meet the unique demands of satellite communications. Among the various AI applications in this fields as depicted in below Fig 2, notable areas include beam-hopping, anti-jamming, network traffic forecasting, handoff optimization and carrier signal detection etc.

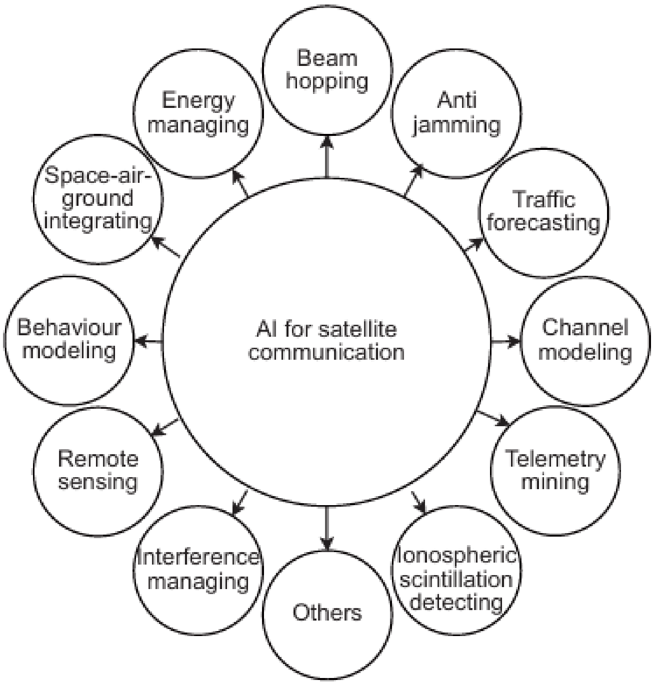

Figure 2 Applications of artificial intelligence for different satellite communication aspects

3.1.1 AI-Based Solutions for Beam Hopping

Beam Hopping (BH) has emerged as a promising technique to manage the dynamic and non-uniform traffic demand across different satellite coverage areas. BH involves dynamically activating a limited number of beams at any given time to meet varying traffic needs as shown in fig 3. Traditional methods of implementing BH have relied on optimization algorithms, but these approaches face several limitations such as high complexity of optimization, long computation times, limited adaptability to traffic fluctuations especially as the complexity of satellite networks grows.

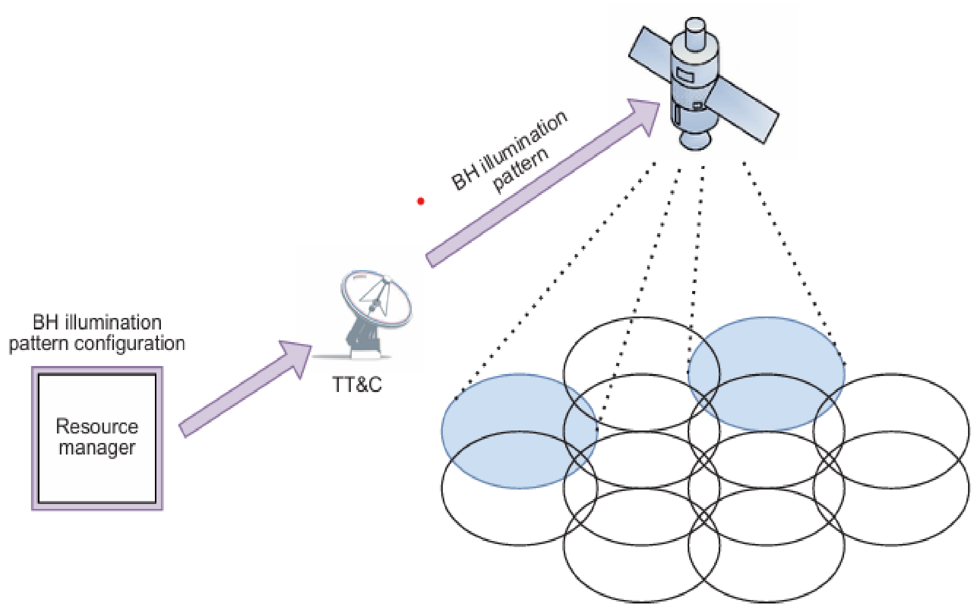

Figure 3 Simplified architecture of beam hopping(BH)

AI and ML are revolutionizing the way beam hopping (BH) is managed in satellite communication systems. Traditionally viewed as a complex optimization challenge, BH has benefited immensely from AI-based approaches, particularly through techniques like Deep Reinforcement Learning (DRL), hybrid learning, and multi-objective deep reinforcement learning. AI-based approaches have shown significant improvements over classical methods. DRL enables the satellite to dynamically adapt to traffic variations by learning optimal beam illumination patterns based on time-varying demands. Studies have demonstrated that DRL can reduce transmission delays by up to 50% and increase throughput by over 10% compared to traditional optimization algorithms [5], [6], [7], [8].

3.1.2 AI-Based Solutions for Anti Jamming

Traditional Anti-Jamming (AJ) techniques in satellite communication, such as Frequency-Hopping Spread Spectrum (FHSS) and Frequency Division Multiple Access (FDMA), have shown limitations in handling increasingly sophisticated jamming attacks. These conventional approaches are often static, designed to handle straightforward jamming by spreading signals over different frequencies or hopping between them to avoid interference as shown in fig 3. However, they struggle against intelligent jamming techniques that can adapt in real-time by altering power, frequency, and modulation strategies. This dynamic jamming creates a major challenge for traditional systems, as they lack the ability to quickly reconfigure and optimize their responses. Moreover, conventional AJ techniques often introduce increased latency, computational complexity, and synchronization delays, which can degrade the overall communication efficiency, especially in scenarios with rapidly changing jamming strategies.

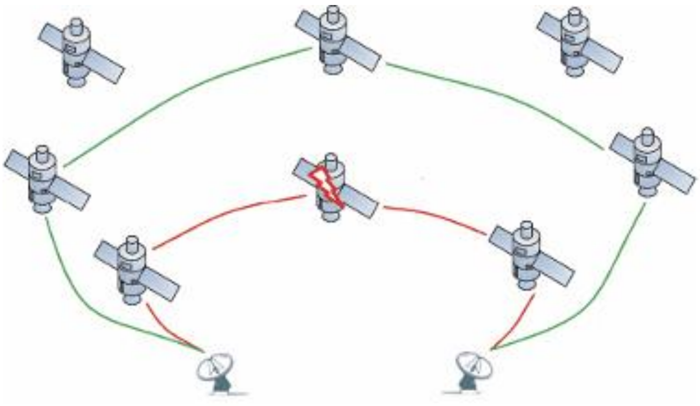

Figure 4 Space-based anti-jamming routing. The red line represents the found jammed path, and the green one represents the suggested path

The integration of AI and machine learning (ML) into AJ systems addresses these limitations by introducing real-time adaptability and predictive capabilities.

- AI-based solutions, such as Deep Reinforcement Learning (DRL) and Q-learning, can model the complex interactions between satellite communication systems and jammers, allowing for dynamic adjustments based on environmental feedback.
- DRL, in particular, has been applied to optimize the selection of communication paths, reducing transmission delays and improving throughput by intelligently predicting jammer behaviour and adjusting accordingly. Additionally, AI techniques with Time Steps inferencing such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) networks enable satellite systems to anticipate jamming attacks by analysing temporal patterns in signal interference, thus enhancing synchronization and reducing response time.
- Game theory models integrated with Reinforcement Learning (RL) have also been developed to manage complex jamming environments. These models treat the interaction between jammers and satellite users as strategic games, allowing the system to find optimal strategies to counteract jammers, even when multiple smart jammers are involved. By combining learning-based approaches with traditional optimization, AI enables satellite communication systems to quickly adapt to changing conditions, maintain secure communication, and ensure more robust anti-jamming measures in an evolving threat landscape. [9], [10], [11]

3.1.3 AI-Based Solutions for Network Traffic Forecasting

Network traffic forecasting is crucial for maintaining reliable communication in satellite applications, given the self-similar nature and Long-Range Dependence (LRD) of satellite network traffic. Traditional Time Series forecasting models, such as those based on Autoregressive Integrated Moving Average (ARIMA) and fractional ARIMA (FARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Vector Autoregression (VAR) face significant challenges due to their high computational complexity, which is not well-suited for the limited computational resources available on satellites.

Moreover, these conventional models struggle with the LRD characteristic of satellite traffic, often leading to inaccurate predictions when employing short-range dependence (SRD) models. In contrast, AI-based solutions offer promising alternatives by efficiently handling the intricacies of LRD while requiring less computational power. Techniques like combining FARIMA with Neural Networks (NNs) and utilizing least-square Support Vector Machines (SVMs) have demonstrated improved accuracy and reduced training times. Additionally, the integration of Empirical Mode Decomposition (EMD) with AI methods allows for the simplification of traffic data, transforming it into more manageable forms while enhancing forecasting speed and precision. This evolution towards AI techniques addresses the limitations of conventional forecasting systems, facilitating more accurate and efficient traffic management in satellite networks [12], [13], [14].

3.1.4 AI-Based Solutions for Handoff Optimization

Handoff optimization in Low Earth Orbit (LEO) satellite networks presents unique challenges compared to terrestrial networks, primarily due to the dynamic connectivity patterns and frequent movement of satellites. Link-layer handoffs are essential for maintaining communication as User Equipment (UE) continuously measures the strength of reference signals from various cells to connect to the strongest signal. Traditional handoff management strategies rely heavily on signal strength and historical Reference Signal Received Power (RSRP) to make handoff decisions, which can sometimes lead to unnecessary transitions.

Researchers have sought innovative approaches to enhance this process, notably by framing the handoff decision as a classification problem. For instance, implemented variants of Convolutional Neural Network (CNN) architectures to analyse the historical RSRP data, leveraging its strong local spatial correlations to improve decision-making accuracy. This AI-based method significantly reduced the number of handoffs by over 25% for more than 70% of the UE, showcasing its effectiveness compared to the conventional "strongest beam" approach, which only achieved a modest 3% reduction in average RSRP. By employing advanced AI techniques, the optimization of handoff management can lead to more stable and reliable communication in LEO satellite networks, addressing the limitations of traditional methods [15].

3.1.5 AI-Based Solutions for Carrier Signal Detection

Carrier signal detection in the frequency domain is critical for wireless communication, as it enables the separation of signals required for modulation, demodulation, and decoding. Traditionally, algorithms for this purpose relied on threshold values, often necessitating human intervention. Although improvements such as double thresholds have been made, these methods still face limitations in accuracy and efficiency.

Recently, Deep Learning (DL) techniques have emerged as powerful alternatives for carrier signal detection. For instance, applied a fully connected Neural Network (NN) for detecting Frequency Shift Keying (FSK) signals, while utilized DL for the blind detection of Morse signals in wideband spectrum data [16], [17].

Advanced this field by employing a Fully Convolutional Network (FCN) model especially the U-NET architecture to detect carrier signals in the broadband power spectrum. In their approach, the broadband power spectrum is treated as a one-dimensional image, with each subcarrier representing a target object. This method reframes the detection problem as a semantic segmentation task, classifying each point in the power spectrum as either a subcarrier or noise [18].

By utilizing a 1D deep FCN, they achieved significant improvements in detection accuracy compared to traditional slope-tracing methods. This integration of AI-based solutions in carrier signal detection reflects a transformative shift towards more efficient and reliable signal processing in satellite communications.

3.2 AI and Machine Learning in Optical Sensing

As the global reliance on high-speed data services continues to increase, the role of optical fibre networks in supporting the infrastructure becomes even more essential. Optical fibres, which are the backbone of Telecom Service Providers/ Internet Service Providers (ISPs), are crucial for data transmission over long distances. However, managing and maintaining these networks is challenging, particularly once the fibres are installed underground or in other inaccessible areas. Over time, external environmental factors, physical damage, or degradation in the fibres can affect network performance, and detecting these issues manually can be inefficient and expensive.

Artificial Intelligence (AI) and Machine Learning (ML) especially the ensemble approach of supervised and unsupervised algorithms is now revolutionizing optical sensing, offering solutions that can vastly improve the monitoring and maintenance of fibre optic networks. Following are the ways by which AI and ML are enhancing optical sensing systems, particularly in their ability to address challenges in real-time monitoring and early detection of network problems:

i. Real-Time Monitoring:

Once optical fibres are installed, it becomes difficult to assess their condition due to their locations, often spanning large distances or being buried. AI and ML techniques allow for continuous real-time monitoring of fibre optic networks, providing insights into the fibre's operational health. These technologies analyse vast amounts of data collected by optical sensors that measure parameters such as signal strength, transmission quality, and potential disruptions.

ii. Early Detection of Issues:

AI models are trained to detect anomalies in network performance. For example, they can identify patterns in signal degradation or data transmission losses that might indicate early signs of damage or wear in the fibre. Machine learning algorithms can differentiate between minor fluctuations and more severe problems, enabling operators to detect issues before they result in complete failures or network outages.

iii. Determining the Nature of the Problem:

Beyond detecting issues, AI and ML's Multiclass Predictive Algorithms are capable of diagnosing the type of problem affecting the optical fibre network. For example, the systems can analyse whether the issue is caused by physical damage to the cables, signal interference, or degradation over time due to environmental factors like temperature or moisture. By pinpointing the root cause, these systems allow for more targeted repairs, saving time and resources.

iv. Proactive Maintenance:

AI-driven predictive models enable predictive maintenance by providing insights into when and where a problem is likely to occur. This allows telecom operators to proactively address issues before they escalate into major disruptions. For example, if the AI system detects a trend that indicates gradual signal loss in a specific section of the fibre, operators can schedule maintenance before the network experiences significant downtime.

v. Cost-Effectiveness and Operational Efficiency:

AI and ML help reduce the costs associated with network maintenance by minimizing manual inspections and enabling precise interventions. Instead of waiting for a failure to occur or conducting time-consuming routine checks, AI can guide maintenance teams to areas that need immediate attention. This not only cuts operational costs but also improves network reliability and customer satisfaction by reducing unplanned outages.

vi. Improved Decision-Making for ISPs:

TSPs/ISPs benefit from AI's ability to analyse massive datasets in real time, making informed decisions about network management. By utilizing AI-based tools, TSPs/ISPs can optimize their network routing, enhance traffic flow management, and improve overall service quality, especially during peak usage periods. In case of potential disruptions, AI can recommend alternate paths for data transmission, ensuring that services remain uninterrupted [23], [24], [25].

3.3 AI for Optical Switching and Networking

3.3.1 AI in Optical Transmission

This section describes application of AI techniques in the physical layer of optical networks I.e., in optical transmission-related issues. AI techniques can help improve the configuration and operation of network devices, optical performance monitoring, modulation format recognition, fibre nonlinearities mitigation and Quality of Transmission(QoT) estimation [23].

3.3.1.1 Characterization and Operation of Transmitters

AI techniques facilitate statistical modeling of individual optical components by including the underlying physics. In all these cases where a deterministic approach results in an impractical computational load, learning mechanisms are becoming a promising and accurate performance improvement tool. With the advent of advanced modulation formats aiming to increase the spectral efficiency, ranging from 16 quadrature amplitude modulation (16 QAM) to 64 QAM and beyond, the need for robust carrier frequency and phase synchronization becomes crucial. At this point, a precise characterization of amplitude and phase noise of lasers is essential. Conventional time-domain approaches perform coherent detection in combination with Digital Signal Processing (DSP) to cope with this issue but as higher order modulation formats are implemented, the accuracy of the phase noise estimation is compromised in the presence of moderate measurement noise. A frame work of Bayesian filtering in combination with Expectation Maximization (EM) is used to accurately characterize laser amplitude and phase noise that outperforms conventional approaches. Results demonstrate an accurate estimation of the phase noise even in the presence of large measurement noise. Presence of large measurement noise. Additional examples of the use of AI techniques in the optimization of transmitters and lasers use simulated annealing to determine the optimal settings in terms of flatness for optical comb sources for ultra-dense WDM passive optical networks, and use of machine learning, genetic algorithms and adaptive control techniques to provide a self-tuning mechanism for mode-locked fibre lasers.

3.3.1.2 Operation of Erabium-doped fibre Amplifier

EDFAs are another optical network component on which AI techniques have been extensively applied. EDFAs are one of the key elements of optical transport networks, capable of extending the reach of the transmitted optical signal by performing amplification of WDM channels in the optical domain. Machine learning techniques offer efficient solutions to a wide range of challenges inherent to the operation of EDFAs within optical fiber transmission. Supervised machine learning is used to statistically model the channel dependence of power excursions in multi-span EDFA networks, learning from historical data. It provides the system with accurate recommendations on channel add/drop strategies to minimize the power disparity among channels. With the arrival of flex-grid networks, in which dynamic defragmentation is often applied to re-optimize spectrum assignment to active connections in order to improve the spectral efficiency, to cope with the power excursion problem in dynamically changing spectral configurations. A ridge regression model is used to determine the magnitude of the impact of a given sub-channel, and a logistic regression is applied to specify whether the contribution will result in an increase or decrease in the discrepancy among post-EDFA powers. Additionally, a novel method for autonomous adjustment of the operating point of amplifiers in an EDFA cascade uses a multilayer perceptron neural network.

3.3.1.3 Performance monitoring

A challenge in network control and management is to adapt to the time-varying link performance parameters, such as Optical Signal to Noise Ratio (OSNR), non-linearity factors, Chromatic Dispersion (CD) and Polarization Mode Dispersion (PMD). This subsection analyzes the suitability of the application of AI techniques in monitoring some of the aforementioned factors. The estimation and acquisition of physical parameters of transmitted optical signals allow network-diagnosis in order to take actions (repairing damages, driving compensators/equalizers or rerouting traffic around non-optimal links) against malfunctions. Application of artificial neural networks in Optical Performance Monitoring (OPM) includes the simultaneous identification of accumulated non-linearity, OSNR, CD and PMD, from eye-diagram and eye-histogram parameters. As an example, Deep Neural Network (DNN), trained with raw data asynchronously sampled by a coherent receiver is used for OSNR monitoring. Results show that OSNR is accurately estimated. Yet, this DNN needs to be configured with at least 5 layers and needs to be trained with 400,000 samples to achieve accurate results, requiring long training time.

3.3.1.4 Receiver and mitigation of Nonlinearities

Currently, the information capacity of fiber optic systems is limited by nonlinear effects of the optical fiber. Extensive research effort has attempted to address mitigation of nonlinearities on the transmission over optical fiber. Among these nonlinearities, nonlinear phase noise (NLPN) is one of the prominent factors. So far this issue has been treated with electronic methods relying on the deterministic information of the fixed fiber link, like maximum likelihood estimation], digital back propagation and stochastic digital back propagation, which may be computationally too heavy for practical implementation. Currently, machine learning techniques are being incorporated to digital signal processing to mitigate nonlinearities in a more efficient way, allowing more accurate symbol detection. As an example, a cognitive digital receiver is able to identify the incoming signal format, QPSK/8PSK/16QAM, without the need to receive a prior control message, thus opening the door to the autonomous modification of the modulation format. Further, machine learning algorithm is used to mitigate NLPN affecting M-ary phase-shift keying(M-PSK) based coherent optical transmission systems.

3.3.1.5 Quality of Transmission (QoT) Estimation

Optical connection (or light path) QoT estimation prior to deployment is particularly relevant in impairment-aware optical network design and operation. QoT estimator tool, the Q-Tool, which computes the associated Q-factors of a set of light-paths, given a reference topology, by combining analytical models and numerical methods. These estimates are relatively accurate, but the necessary high computing time to perform the calculations makes this tool impractical in scenarios where time constraints are important. Several approaches propose cognitive techniques to solve this drawback. As an example, a QoT estimator capable of exploiting previous experience and thus, provide with fast and correct decisions on whether a light-path fulfils QoT requirements or not. It is based on Case-Based Reasoning (CBR), an artificial intelligence mechanism that offers solutions to new problems by retrieving the most similar cases faced in the past whether by reusing them or after adapting them. Cases are retrieved from a Knowledge Base (KB), which can be static or optimized with learning and forgetting techniques. Results for CBR relying on an optimized KB show an excellent rate of successful classification of light paths into high/low QoT categories and more important, up to four orders of magnitude faster than the Q-Tool mentioned above.

3.3.2 AI in Optical Networking

AI presents several opportunities for automating operations and introducing intelligent decision making in network planning and in dynamic control and management of network resources, including issues like connection establishment, self-configuration and self-optimization, through prediction and estimation by utilizing present network state and historical data. In this section, we review these applications as well as use cases of AI in Optical Burst-Switched networks (OBS), in Passive Optical Networks (PONs) and intra-data centre networks [23].

3.3.2.1 Optical Network Planning

Optical network planning involves tasks like designing the physical topology of the network and ensuring survivability while minimizing costs. search algorithms and optimization theory have been widely used for optical network planning and dimensioning, usually complemented or extended with local search algorithms and metaheuristics like simulated annealing, swarm optimization and genetic algorithms. Genetic algorithms are used to address issues in an opaque optical transport network, dimensioning dynamic WDM ring networks. A related optimization problem like minimizing the number of all-optical regenerators, is tackled by with genetic algorithm, which also jointly solves the Routing and Wavelength Assignment (RWA) problem while ensuring the QoT for the light paths to be established. Swarm Optimization(PSO) algorithm is used to solve the problem of resource allocation based on the signal-to-noise plus interference ration optimization in a hybrid wavelength division multiplexing/ optical code division multiplexing network under quality of service restrictions and the energy efficiency constraint problems. Another example of the use of AI in resource allocation is the message scheduling algorithm, based on the k-means clustering algorithm, which ad dresses both message sequencing and channel assignment for a WDM star network. Based on the produced clusters, the scheduling algorithm manages to avoid scheduling consecutive messages to the same destination which harms the channels' utilization.

3.3.2.2 Connection Establishment

Metaheuristics like simulated annealing and evolutionary methods like genetic algorithms or particle swarm optimization, are effective in solving hard optimization problems because they are less likely to become trapped in local optima. Therefore, these methods are useful to solve the optical connection (light path) establishment problem in optical networks. In WDM networks, this involves searching a combination of route and available wavelength, and is so called the Routing and Wavelength Assignment (RWA) problem. In Elastic Optical Networks(EONs), it involves searching for a route and a portion of available spectrum and even a modulation format, i.e., solving the Routing and Spectrum Allocation (RSA) or the Routing, Modulation Level and Spectrum Allocation (RMLSA) problems.

3.3.2.3 Network Reconfiguration: Virtual Topologies

The virtual topology is the set of optical connections (or light paths) established in a network. It does not have to be statically configured, but it can be dynamically reconfigured in order to better adapt to evolving traffic demands with some objectives like reducing energy consumption, network congestion, end-to-end delay or blocking probability or trying to ensure Quality of Transmission (QoT), etc. For that purpose, two nature inspired heuristics, GA and ACO, are used to obtain a survivable mapping of a given WDM virtual topology. Feasible solutions are obtained even for large topologies when integer linear programming methods cannot. Also, a multi-objective genetic algorithm to design virtual topologies with the aim of reducing both the energy consumption and the network congestion can be used.

3.3.2.4 Software Defined Networking

The Software Defined Networking (SDN) paradigm, which decouples control and data planes, and enables programmability on the former plane, has aroused the interest of both industry and research communities by allowing networks managers to manage, configure, automate and optimize network resources via software. In the context of SDN over optical networks, a correct mapping of the underlying topology at the control plane level is crucial. Following this requirement, a novel SDN-based cost-effective topology discovery method, allowing transparent optical networks to automatically learn physical adjacencies between optical devices, this is achieved by means of a test-signal mechanism–by exchanging and verifying identifier information between discovery agents– and the OpenFlow protocol, resulting in correct mapping of the topologies in low total times. Also, neural network-based methods are used for planning of an SDN-based optical network which are able to predict link performance in correlation with the OSNR.

3.3.2.5 Application in Optical Burst Switching

Optical Burst-Switched (OBS) networks have also taken advantage of artificial intelligence, and in particular, of ma chine learning techniques. OBS architecture takes advantages of learning automata to achieve self-awareness, self-protection and self-optimization, consequently reducing burst loss probability significantly. Machine learning has been used in Q-learning in order to solve the path and wavelength selection problem, or by exploiting the feedback loop to control the re-transmission rate of bursts that are lost. Moreover, variations of the TCP protocols to enhance the performance of OBS network also utilizes supervised and unsupervised learning techniques.

3.3.2.6 Applications in Intra-Datacentre Networking

Intra-datacentre (DC) networks are also embracing machine learning techniques in order to improve performance. For instance, in hybrid-switching-based DCs, where an electrical packet switched and an optical circuit-switched network live together, machine learning-based flow classification may be a decisive solution to improve speed and accuracy, besides improving adapt ability to traffic dynamics. As an example, a neural network flow classifier at the edge of the network, combined with an SDN centralized controller able to take advantage of this classification outcome along with its global view of the resources.

3.3.3 AI for Intelligent Networks

3.3.3.1 Network Planning and Design

AI is transforming network planning and design by using advanced analytics and predictive modelling to enhance cost efficiency and optimize Total Cost of Ownership (TCO). Through machine learning techniques, AI systems can perform high-accuracy traffic forecasts and predict Key Performance Indicators (KPIs), enabling service providers to anticipate demand and address potential issues proactively. For instance, AI-driven models can identify network bottlenecks and provide recommendations for load balancing, thus improving network performance. By analysing live radio measurements and subscriber traffic patterns, AI tools facilitate data-driven decisions, ensuring efficient utilization of existing resources and guiding strategic 5G network expansions. This optimization leads to enhanced service quality, reduced operational costs, and an overall more reliable communication network infrastructure [22].

3.3.3.2 Network Operation

AI is transforming network operations by driving the shift towards zero-touch automation, where manual interventions are minimized, and processes are automated end-to-end. AI algorithms analyse vast amounts of real-time data from network activities, enabling service providers to make augmented, data-driven decisions. AI/ML and Generative AI enable real-time detection of issues like faults and SLA breaches, diagnose problems, provide recommendations, and take actions to resolve network issues. This results in predictive and proactive network management, where potential issues are identified and resolved before they impact service quality. Through techniques like anomaly detection and predictive analytics, AI helps operators anticipate faults, optimize resource allocation, and streamline maintenance tasks. This not only improves operational efficiency but also enhances business agility, as networks can quickly adapt to changing demands, reduce downtime, and deliver a more reliable user experience. The integration of AI in network operations enables dynamic optimization, self-healing capabilities, and faster adaptation to new services, paving the way for fully autonomous networks [22].AI is transforming network operations by driving the shift towards zero-touch automation, where manual interventions are minimized, and processes are automated end-to-end. AI algorithms analyse vast amounts of real-time data from network activities, enabling service providers to make augmented, data-driven decisions. This results in predictive and proactive network management, where potential issues are identified and resolved before they impact service quality. Through techniques like anomaly detection and predictive analytics, AI helps operators anticipate faults, optimize resource allocation, and streamline maintenance tasks. This not only improves operational efficiency but also enhances business agility, as networks can quickly adapt to changing demands, reduce downtime, and deliver a more reliable user experience. The integration of AI in network operations enables dynamic optimization, self-healing capabilities, and faster adaptation to new services, paving the way for fully autonomous networks [22].

3.3.3.3 Network Optimization

AI is revolutionizing network optimization by enabling real-time diagnostics and continuous performance enhancements across communication networks. Utilizing advanced algorithms, AI systems scan all network cells in minutes, rapidly identifying performance issues with high precision. This proactive approach allows for the early detection of up to 50% more issues compared to traditional methods, significantly reducing downtime and improving network reliability. AI-powered diagnostics leverage machine learning models to analyse large datasets from various network elements, pinpointing bottlenecks, predicting anomalies, and recommending corrective actions. This results in enhanced operational efficiency, with reported improvements of up to 30%, as AI-based optimization dynamically adapts to traffic changes, balances loads, and ensures optimal resource utilization. Ultimately, this leads to improved service quality, reduced operational costs, and a more resilient network infrastructure [22].

3.3.3.4 Network Security

AI is playing a critical role in enhancing the security of 5G networks by automating the detection and mitigation of complex cyber threats. With its ability to analyse massive volumes of network data in real-time, AI can identify zero-day attacks—new vulnerabilities that traditional systems may fail to detect—by recognizing unusual patterns and behaviours indicative of potential threats. Machine learning models are trained to predict upcoming attacks by analysing historical attack data and identifying early warning signs, enabling pre-emptive action. Additionally, AI-driven solutions can detect ongoing attacks with high precision, isolating affected components to prevent the spread of malicious activities. By utilizing advanced techniques like deep learning and reinforcement learning, AI systems can also dynamically test and deploy new defence mechanisms at runtime, adapting to evolving threats and ensuring continuous protection. This proactive and adaptive approach significantly strengthens the overall security posture of 5G networks, safeguarding them against both known and emerging threats [21].

3.3.4 AI for Improving Wi-Fi Performance

The transformative impact of AI on Wi-Fi extends far beyond immediate performance enhancements, setting the stage for a new era of intelligent networking. Some of the capabilities of AI-powered Wi-Fi are:

- **Predictive Analytic:**

Utilizing machine learning algorithms to sift through historical data, AI Wi-Fi systems forecast future network demands. This foresight allows for anticipatory adjustments to sustain peak performance, illustrating a proactive approach to network management.

- **Automated optimization:**

AI Wi-Fi continuously monitors the network environment, automatically tweaking parameters such as power levels, channel assignments, and load balancing. This ensures optimal performance and user experience without manual intervention.

- **Intelligent troubleshooting:**

By implementing AI-powered diagnostics, the time to resolve network issues is drastically reduced. These systems accurately identify the root causes of problems, often rectifying them autonomously, thus minimizing the need for human intervention.

- **Enhanced security:**

Leveraging AI and machine learning, Wi-Fi networks are better equipped to detect and neutralize security threats. This advanced capability ensures comprehensive protection for both enterprise data and connected devices.

- **Seamless connectivity:**

AI in Wi-Fi facilitates smooth transitions between access points and dynamically allocates resources based on real-time user demand. This feature is crucial for maintaining consistent connectivity, especially for mobile users and IoT devices [26].

3.3.5 Intelligent Routing

Network routing typically consumes significant bandwidth and resources, particularly when selecting optimal paths to ensure efficient data transmissions from the source to the destination in large-scale IoT environments, where frequent updates are necessary. Introducing GAI into network routing can enhance the efficacy of choosing and optimizing routing algorithms for certain network objectives by simulating, creating, and analysing synthetic network scenarios. An example of this is exploiting a one-shot conditional generative routing model to perform one-shot routing to the pins within each network, and the order in which the networks need to be routed is learned adaptively. Another example of GAI in routing solutions for different network status distributions and topology is exploiting a transfer RL algorithm to improve training efficiency by rapidly transferring knowledge.

3.3.6 Cloud-Based Assistive Approach

When it comes to the telecommunications cloud, the following applications are best suited for the incorporation of AI:

- By optimizing the network and automating the operations, costs can be reduced, and productivity increased.
- Big data-based analytics provide for effective value mining and risk protection in the context of large network data.
- Implementing unified open interfaces or standards for interoperability, as well as layer decoupling and control of networking resources, via hybrid infrastructure.
- Preferring sovereign cloud providing air-gapped solutions that are designed around open cloud strategy and use leading open source components in its platform and managed services. The underlying solution would then be 'Secure by Default'

4.0 Generative AI in Telecom

i. Customer Services

Generative AI can help transform contact centers into a competitive advantage by reducing call average handle time (call duration) and first call resolution (get the right answer first time), improving agent productivity and satisfaction, lowering costs, and helping to identify business improvement opportunities using conversational insights. Customer care agents and supervisors can better understand and respond to customer needs by using real-time agent assist solutions. In addition, IVR Call automation leverages generative AI to automatically analyze call transcripts, design optimal interactive voice response flows, and generate the required IVR call flows to increase containment rates and dramatically reduce contact center costs. By analyzing customer preferences and usage patterns, generative AI using Large Language Models such as Generative Pre-Trained Transformers (GPT), Language Model for Dialogue Applications (LaMDA), Pathway Language Models (PALM) personalizes service recommendations and promotions. It enables proactive support by predicting potential issues like outages, ensuring timely resolution and an improved customer experience. For example, a Latin American telecom provider is upgrading its AI-powered chatbots to better support agents, aiming for a 15–20% reduction in operational costs. These chatbots can handle routine inquiries, provide instant responses, and redirect complex issues to human agents, reducing customer wait times. Additionally, the telecom company leverages generative AI to summarize client interactions from voice calls and written communications across various use cases. By integrating generative AI, telecom companies can achieve faster resolutions, boost customer satisfaction, and drive operational efficiencies in their service models.

ii. Call Centre

AI-driven Chabots provide accurate and personalized customer support, reducing response times and costs. They gather customer feedback for refining services and improving satisfaction, while ensuring efficient and scalable support solutions.

iii. Intelligent Infrastructure Planning

Generative AI revolutionizes infrastructure deployment by analyzing geographic and demographic data to identify optimal locations for installations like cell towers and fiber networks. It simulates network configurations to improve design, capacity planning, and resource allocation, enhancing cost efficiency and reliability.

iv. Boost Revenue through Personalization

Generative AI is transforming marketing and sales by enabling hyper-personalization, uncovering deeper customer insights, and accelerating content creation. It uses advanced models to analyse customer data, such as demographics, preferences, and behaviour, to craft tailored messages and campaigns. For instance, a European telecom company leverages generative AI to identify new sales leads from customer calls, achieving over a 10% conversion rate in its pilot project. The AI model processes standard marketing messages alongside customer data like household details, device type, and location. It incorporates cognitive biases, such as messaging that evokes scarcity (e.g., limited-time offers) or emphasizes authority (e.g., endorsements or industry expertise), to target microsegments effectively. Additionally, generative AI with use of Generative Adversarial Networks (GAN or Super GAN) models automates the creation of personalized visual media and communication, ensuring that campaigns resonate with individual customers. By doing so, companies can improve customer engagement, enhance lead generation, and optimize sales strategies, achieving higher efficiency and better ROI.

v. Personalized Experience

In addition to further improvements in customer call centre interactions, generative AI can deliver improved personalization in ecommerce interactions — a big factor in helping customers sort through their choices of phones and calling plans. Personalization is also important for lowering churn, offering relevant new services, and managing the customer lifecycle. For example, generative AI could enable CSPs to produce marketing campaign content customized for select themes, and target individual customers with customized text and images.

vi. Human-Readable Content

Gen AI is used in creation of human-readable content by automating tasks like generating, summarizing, and translating text, images, audio, and video. It enables businesses to streamline processes across marketing, customer service, and operations by producing customized text-based outputs such as service-level agreements, troubleshooting guides, and training materials. In telecommunications, GenAI can create or interpret technical documentation, generate network characteristics from textual inputs, and even assist through dialogue-based systems like ChatGPT. By making content creation more efficient and accessible, GenAI enhances productivity and ensures consistency across communication channels.

vii. Machine-Readable Content

Generative AI plays a pivotal role in creating machine-readable content by analysing raw data, such as mobile network logs or configuration parameters, to generate outputs like coverage maps, incident detection reports, or optimized resource allocations. It can synthesize additional data to augment limited datasets, addressing challenges like data scarcity due to low network activity or technical issues. For instance, in networks, GenAI can simulate missing data frames in virtual environments or during poor connections, ensuring seamless user experiences. This capability enhances data utility for training models and improves network performance and resilience.

viii. Digital Twins

Generative AI transforms the creation and use of digital twins by enabling more efficient and realistic virtual representations of physical systems, processes, or objects. Traditionally, building digital twins required extensive coding, programming resources, and data collection, which was both time-consuming and resource-intensive. Generative AI simplifies this process by training models on the behavior of physical counterparts, automating the generation of digital twin behaviors and making them more reflective of real-world dynamics by leveraging Cognitive Intelligence using structured, semi structured and unstructured data. It can also create streamlined digital twins that accurately simulate key functions while reducing computational costs, enabling faster response times. This advancement makes digital twins more accessible and affordable, empowering industries to optimize, test, and validate systems with minimal risk to live networks.

ix. Semantic Communication

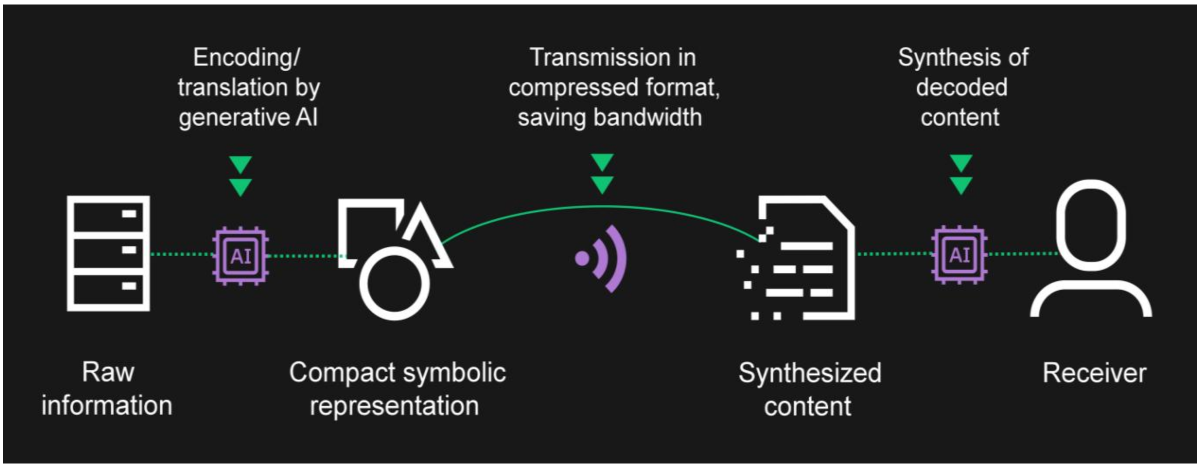

Figure 5 Semantic Communication

Generative AI significantly enhances semantic communication by enabling the compact encoding of raw data into compressed, multi-dimensional symbols that can be transmitted efficiently and later synthesized at the receiver end. This approach minimizes bandwidth requirements while maintaining the ability to reconstruct understandable content for end users. Generative AI can assist in both encoding and decoding processes, improving transmission efficiency in mobile networks. However, the computational and storage demands of these AI processes, particularly in resource-constrained environments like Radio Access Networks (RANs), necessitate innovative strategies such as algorithm compression or distributed computing at the network edge for scalable implementation.

x. Network Deployment

Generative AI can provide coding assistance and automate testing tasks – to free up engineers' time and allow them to focus on more complex, meaningful work that makes the best use of their time and talents.

xi. Fraud Protection

Revenue leakages pose a significant challenge for telcos, impacting up to 10% of their revenues and translating to nearly a hundred billion in annual lost revenue across the industry. Addressing this issue involves manual processes and analysing disparate applications and data sources in various formats - a daunting task. However, generative AI offers a powerful solution by rapidly analysing these disparate data sources to automatically discover and remediate sources of revenue leakage, potentially saving telcos millions in lost revenue.

Additionally, broadening the spectrum of data sources, including live data access through LLM plugins, will enrich contextual insights and improve accuracy. In parallel, fraud attacks continue to rise and increase in sophistication, costing businesses financially and severely impacting brand and reputation. As more services and transactions expand online, businesses need tools to validate that their users are well- meaning human beings and not malicious bots and fraudsters

xii. Generate Powerful Sales Content

Sellers are leveraging generative AI to automate manual work and help them seize opportunities faster. Telecom b2b sales teams are usually overwhelmed with the manual, error prone, and time- consuming work needed to respond to RFPs, spending precious hours on repetitive, undifferentiated tasks.

xiii. Simplifying Network Operation

Generative AI provides the connective tissue to break down network infrastructure silos like RAN, Core, IMS, enabling zero-touch operations. It leverages run-books, configures, tickets and docs to detect issues, diagnose root causes, recommend fixes and automate remediation - reducing triage times and improving customer experience.

xiv. Generative AI for Threat Response

It is understandable that any malicious user can use AI to quickly launch multipronged attacked on critical national infrastructure. To secure such attacks, organization should be using generative AI to be able to respond the attack as it evolves. For this it is imperative that the security operations of organizations can take help of telco trained generative AI tools to:

- Showcase how the attacker entered the telecom network and moved laterally.
- And respond in real time to the attacks.

Subsequently, it is a fact that telecom security is a complex topic cannot be left to the relatively new (security operations centre) engineer who takes time to understand the attack, its kill chain and possible remediation.

Hence, a telco-trained generative AI system will be able to assist the SOC analysts to be pinpoint the affected elements; the technique used by the attacker and either remediate the attack automatically or provide guided responses to the SOC analyst to take the appropriate threat remediation steps.

xv. AI for Securing the Telecom Network

A telco-trained AI intelligence system promptly correlates data from various security controls and does log analysis across complex telecom networks. This results in unveiling critical details about attack attempts on the core, RAN, or transport network, showcasing the prowess of AI-driven investigative approaches in security operations for service providers and critical infrastructure enterprises.

The AI Security system can be used, for example, to create a digital identity for users and network entities. This will speed up the detection of new threats for which there were no "rules" defined.

Using network digital twin, the AI Security system provides comprehensive visibility across endpoints, network, cloud and email provides coverage of all network elements, devices and connections from telco Radio Access Network (RAN), Transport and Core networks. The use of AI and advanced analytics help reduce workloads of correlating and contextualizing security incidents and achieve faster threat detection and response.

The AI security system can map the attack and its complete kill chain and showcase how the attacker entered the telecom network and moved laterally.

5.0 AI for IoT

Emerging paradigms like the Internet of things (IoT), Industrial Internet of Things (IIoT), Artificial Intelligence enabled Internet of Things (AIoT) leveraging edge computing and embedding Artificial Intelligence at IoT device level, Industry 4.0 or the tactile Internet, impose stringent requirements on networks, such as low latency, and high bandwidth, availability and security, thus posing a significant challenge. The combination of 5G mobile communications systems with high-speed fault-tolerant fiber backhaul infrastructures will be key enabling technologies for these networks. End-to-end latency for some applications can be limited to a few milliseconds (e.g., 1 ms for tactile internet). Thus, the distance between the edge and computing resources must be limited to some tens of kilometers, and a decentralized service platform architecture based on Mobile Edge Computing (MEC) or Fog Computing (FC) is required. However, the integration of various computing paradigms (MEC, Fog and cloud) involves the development of integrated resource management, task allocation and failure handling techniques, to name just a few. Therefore, the joint allocation of computing and networking resources (also including inter datacenter networking) is receiving increasing attention. AI is expected to play a key role to facilitate efficient joint operation of network and computing devices, performing tasks like Virtual Network Function (VNF) distribution, task allocation, predictive caching and interpolation/extrapolation of human actions, and thus enhancing performance and providing better support for IoT and tactile Internet applications. For example, novel tactile Internet capable PON and a dynamic wavelength and bandwidth allocation method can incorporate a mechanism to predict the traffic load to vary the number of active wavelength channels in the network, and prioritize the transmission of tactile Internet traffic (vs. other traffic) to comply with delay requirements [25], [26].

5.1 AI Enabling Intelligent IoT Endpoints and Edge

IoT devices are increasingly generating large amounts of data, much of which ultimately needs to go to the cloud. Although 5G solves issues around the physics of transmission. AI helps in processing massive amounts of raw data at the edge to reduce data size. This can be easily seen in vision-driven applications such as autonomous vehicles and drones.

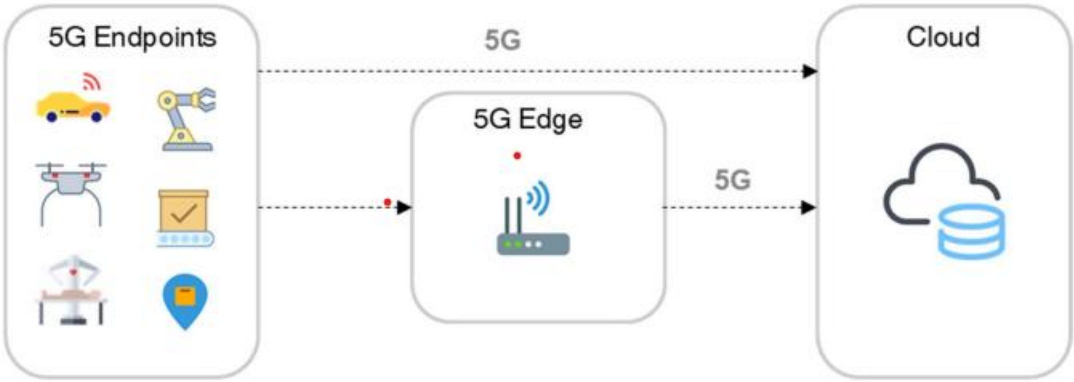

Figure 6 AI Enabling Intelligent IoT Endpoints and Edge

In many implementations, endpoints lack 5G due to cost and power constraints. Instead, they connect to intelligent 5G edge devices such as IoT gateways and CPEs enabled with mMTC. These devices collect endpoint data, filter and process it, and provide secure upstream and downstream channels. The devices can be potentially used in multiple scenarios, including for low-latency Untethered XR devices, industrial machines and others. Effectively, 5G IoT gateways will be edge servers loaded with AI capabilities to facilitate real-time devices, data management, control, analytics and action. AI-empowered drones and robots are good examples of these types of endpoints. They show potential in various industrial settings, including routine inspections across extensive and dangerous environments [25], [30], [31].

6.0 Challenges to AI Security

AI has great potential to build a better, smarter world, but at the same time faces severe security risks. Due to the lack of security consideration at the early development of AI algorithms, attackers are able to manipulate the inference results in ways that lead to misjudgment. In critical domains such as communication networks, security risks can be devastating. Successful attacks on AI systems can endanger personal safety and national security. To mitigate AI security risks, AI systems design must overcome five security challenges:

i. Software and hardware security:

The code of applications, models, platforms, and chips may have vulnerabilities or backdoors that attackers can exploit. Further, attackers may implant backdoors in models to launch advanced attacks. Due to the inexplicability of AI models, the backdoors are difficult to discover.

ii. Data integrity:

Attackers can inject malicious data in the training stage to affect the inference capability of AI models or add a small perturbation to input samples in the inference stage to change the inference result.

iii. Disparate Data Sources Integration:

Data Integration from multiple data sources including CRM, mobile app/web, images, video generated from camera, logs, geospatial, intelligent networks, data usage, SMS, emails etc.

iv. **Big Data Characteristics and Volumetric and Compute Hungry Deep Learning Algorithms:**

Generating realtime inferencing from both Structured and Un Structured Data for Cognitive Intelligence over compute intensive Deep Learning Algorithms such as CNN, Transformer Algorithms such as LLM's based on GPT architecture.

v. **Model confidentiality:**

Service providers generally want to provide only query services without exposing the training models. However, an attacker may create a clone model through a number of queries.

vi. **Model robustness:**

Training samples typically do not cover all possible corner cases, resulting in the insufficiency of robustness. Therefore, the model may fail to provide correct inference on adversarial examples.

vii. **Data privacy:**

For scenarios in which users provide training data, attackers can repeatedly query a trained model to obtain users' private information [21].

viii. **Adversarial Attacks on Network Optimization:**

AI systems in telecom often manage network traffic, allocate spectrum, and handle resources. Attackers can trick these systems, causing network congestion, poor service quality, or even service outages.

ix. **Real-Time Decision Manipulation:**

AI systems in telecom make quick decisions for tasks like call routing, fraud detection, and fault prediction. If attackers manipulate inputs or delay responses, it can lead to disruptions or financial losses.

x. **Scalability of Security:**

Telecom networks are huge and complex. It's challenging to scale AI security across so many devices, protocols, and regions. New solutions are needed to provide consistent protection everywhere.

xi. **Supply Chain Vulnerabilities:**

Many AI systems in telecom depend on third-party hardware and software. Compromised components in the supply chain can introduce vulnerabilities that are difficult to detect and mitigate, especially in distributed operations.

xii. **Regulatory and Compliance Challenges:**

Telecom networks operate under strict regulatory frameworks. Ensuring that AI systems meet these requirements while maintaining security and privacy is not easy and needs careful planning.

7.0 Types of AI Security Attacks and Defence Mechanisms

AI systems face various security threats, which can be broadly categorized into four main types:

i. **Evasion Attacks:** Attackers craft adversarial examples to manipulate model predictions. To mitigate these security risks, defence techniques are:

- Network Distillation
- Adversarial Training

- Adversarial Example Detection
- Input Reconstruction
- DNN Verification

ii. **Poisoning Attacks:** Malicious data is injected into the training set to alter model behavior. Defence techniques for poisoning attacks are:
- Training Data Filtration
- Regression Analysis
- Ensemble Analysis

iii. **Backdoor Attacks:** Attackers implant hidden triggers in models, allowing them to control outputs when specific inputs are provided. Defence techniques for backdoor attacks are:
- Input Pre-processing
- Model Pruning

iv. **Model Extraction Attacks:** Attackers attempt to replicate a model's functionality through repeated querying, effectively stealing the model. Defence techniques for model extraction attacks are:
- Private Aggregation of Teacher Ensembles(PATE)
- Differentially Private Protection
- Model Watermarking

v. **Data Inference Attacks:** Attackers aim to extract sensitive information from AI models, particularly when user data has been used for training. Defence techniques for the data Inference attacks are:
- federated learning
- homomorphic encryption
- differential privacy

vi. **Trojan Attacks:** Attackers compromise the AI system during development or deployment by embedding Trojan code. This can activate harmful behaviours under specific conditions. Defence techniques for the Trojan attacks are:
- Static and Dynamic Code Models
- Model Behaviour Analysis

vii. **Resource Exhaustion Attacks:** Also known as Denial-of-Service (DoS) attacks, these target the computational resources of AI systems, causing slowdowns or crashes. Defence techniques for Resource exhaustion attacks are:
- Rate Limiting
- Load Balancing
- Anomaly Detection

8.0 Case Studies On AI Applications for Enhancing Customer Experiences

Case Study 1: Wipro Unlocks the Power of Network Digital Twins

Digital twins enable telecom companies to simulate physical network changes, analyse performance, and validate decisions—enhancing operational efficiency and network quality.

Issue: Wipro was challenged with network change management to test network configurations before deployment and identify potential issues that save time and cost. Another issue was analysing and predicting network performance to analyse to prevent quality degradation. In addition, telecom companies need to ensure their Radio Access Network (RAN) slices deliver on their Service-Level Agreements (SLAs) to fulfil business contract requirements.

Solution: To address these challenges, Wipro built a telecom network digital twin, a platform for developing OpenUSD applications for industrial digitalization and generative physical AI. The solution enabled 5G new radio (NR) traffic steering and slice SLA assurance. Wipro's AI/ML model predicts SLA adherence of RAN slices and suggests necessary steps to avoid SLA violations. This improved network capacity and resource utilization for telecom companies while enhancing network quality of service with fewer dropped calls for customers [19], [20].

Case Study 2: Infosys Transforms Network Operation Centres and Automates Network Design

Issue: Telecom companies are challenged with meeting Service-Level Agreements (SLAs) for customers that ensure high network quality of service. This includes quickly troubleshooting network devices with complex issues, identifying root causes, and resolving issues efficiently at their Network Operations Centre (NOC). Network architects, engineers, and IT professionals manually retrieve and customize Topology and NOC processes, minimize network downtime, and optimize network performance.

Solution: Infosys developed an automated tool to generate standard TOSCA templates. The generative AI- powered solution achieved 28.5% lower latency and 15% absolute improvement in accuracy. This frees network service designers, as well as OSS solution architects and directors, to design carrier-grade networks faster [19], [20].

Case Study 3: ServiceNow Automates Network Planning and Operations

Issue: ServiceNow was challenged with distilling and actioning on volumes of complex technical data generated from wireless network incidents. The company also needed to meet diverse network services, local configurations, and rulings.

Solution: To improve network operations, ServiceNow used generative AI to summarize network incident data. The solution reduced Mean Time to Resolution (MTTR), tailored communication to enhance IT team satisfaction, and efficiently prioritized high-risk incidents to reduce disruption to customer service. For example, in the case of a fibre cut, ServiceNow's generative AI solution can decipher technical jargon, distils complex information into clear and concise summaries, and speed up time to resolution. This not only drives cost savings, but also improves customer experiences by minimizing service disruptions. ServiceNow also built a network configuration template for network design and fulfilment. The solution improves time to market for new wireless networks; increases customer loyalty with fast, accurate service delivery; and reduces manual errors that lead to delivery delays, customer dissatisfaction, and costly corrections [19], [20].

Case Study 4: Bharti Airtel's Next-Gen AI-powered network platform - A-SON

Issue: Airtel was challenged with building a system that works autonomously 24*7 to manage network degradation and customer experience in closed loop manner, especially for self-identification of issues to optimize the network.

Solution: Bharti Airtel Limited designed & deployed AI driven A-SON (Self Optimizing Network) solution, which can predict the problems or issues that the networks will face ahead of time, and ensure that the network teams can take necessary action to resolve the issue. This helps in delivering seamless network and connectivity services round the clock and ensures that Airtel customers get the best voice and data experience across the country.

Case Study 5: Deustsche Telekom enhances customer support

Issue: Deutsche Telekom, a leading integrations telecommunications company, has over 250 million customers and receives millions of requests every year.

Solutions: Deutsche Telekom is using Amazon SageMaker and Amazon EC2 Inf2 instances to process millions of customer requests and keep costs down to process customer support in real-time. They created services and digital agents to help alleviate the load of those customers, and are building LLM applications to create a more natural response for their customers. Costs associated with generative AI solutions are significant owing to the computational power required. Using Inferentia 2 instances Deutsche Telecom was able to achieve 25% relative Improvement on the non-functional requirements such as throughput latency at a fraction of the cost. Generative capabilities help agents retrieve information real time as opposed to having to wait in several interactions or raising tickets and then getting them answered by different sectors. They consolidate all the support at the same time helping customers get faster solutions.

Case Study 6: Nokia Uses GenAI XDR to secure the critical telecom networks and respond to telecom threats in real time

Issue: Telecommunications security is inherently complex, requiring security analysts in Security Operations Centres (SOCs) to efficiently manage security incidents while also possessing deep expertise in telecommunications networks. With 5G making the network more complex, analysts struggle to keep up and make sense of all the incoming data, making it increasingly difficult to get the complete picture and generate actionable threat intelligence. In addition, ensuring continuous network operation is crucial in the 5G era for critical services like autonomous vehicles and smart grids, which are vital for public safety and economic stability.

Solution: To address these challenges, Nokia, in partnership with Microsoft, has been leveraging AI and automation to enhance the award-winning security orchestration software suite, Nokia NetGuard Cybersecurity Dome. This telco-centric solution is built on an Extended Detection and Response (XDR) architecture, providing comprehensive visibility across the entire telco network, covering Radio Access, Transport, and Core domains. The integration of AI and advanced analytics significantly reduces the workload of correlating and contextualizing security incidents, enabling fast and accurate threat detection and response.

The new telco-centric generative AI assistant integrated into Nokia NetGuard Cybersecurity Dome further enhances XDR capabilities by quickly analysing vast amounts of information related to cyber threats. This assistant is based on large language models within Microsoft Azure OpenAI Service, trained with insights from 5G network architecture, 5G security practices, and Nokia’s telco domain expertise. The training includes information from 3GPP and NIST network architecture specifications, 5G topology spanning RAN, Transport, and Core, and adversary tactics from MITRE ATT&CK and FiGHT (5G Hierarchy of Threats). Nokia is providing telco-centric XDR capabilities that result from the extensive 5G telco security knowledge and experience in secure hybrid-cloud deployments, ensuring faster threat detection and response to enhance the security posture of telecom operators.

Case Study 7: ASTR – AI-Powered SIM Verification System by the Department of Telecommunications

Issue: The growing misuse of telecom networks through fraudulent SIM card connections posed a serious challenge to the integrity of India's telecommunications ecosystem. Multiple SIM connections linked to the same individual led to cyber frauds, security threats, and identity misuse. The Department of Telecommunications (DoT) needed an advanced automated solution to detect and eliminate such fraudulent connections effectively.

Solution: To address this challenge, DoT has developed a powerful AI/ML based engine called ASTR (Artificial Intelligence and Facial Recognition powered Solution for Telecom SIM Subscriber Verification) to detect mobile connections taken on fake/forged documents to weed them out from the telecom ecosystem. As on 31.03.2024, 61.47 lakh mobile connections have been disconnected after failing reverification.

9.0 Conclusion

Artificial intelligence (AI) is rapidly transforming the telecommunications industry, offering AI-powered solutions that enhance network performance, customer experience, and security. As AI technology continues to evolve, it holds the potential to revolutionize the industry, making it more efficient, reliable, and customer-centric. The integration of AI in telecommunications is poised to reshape the industry, driving significant advancements in connectivity, operational efficiency, and service personalization.

AI-driven techniques hold great promise across various applications, including network automation, capacity planning, enhanced security, energy efficiency, customer insights, predictive maintenance, and service assurance. By leveraging AI, communication networks can become more intelligent, adaptive, and capable of meeting the growing demands of modern digital communication. As telecommunications companies embrace AI technologies, they unlock new opportunities to optimize operations and enhance customer engagement in the digital era.

However, while AI offers numerous benefits, challenges remain, such as scalability, interpretability, and privacy concerns. Developing scalable AI models, ensuring transparency in AI-driven decisions, and safeguarding user privacy must be key priorities for future research and development. The establishment of industry standards and benchmarking frameworks will be crucial to ensuring responsible AI deployment in communication networks. Additionally, addressing infrastructure costs through strategic investments—such as securing GPU supplies, improving power and land availability, and developing shared AI infrastructure—can accelerate AI adoption across the industry.

Collaboration between industry stakeholders, academic institutions, and regulatory bodies is essential to developing best practices, ethical guidelines, and policies that govern AI in telecommunications. By addressing these challenges and leveraging AI responsibly, telecom operators can enhance network performance, deliver personalized experiences, and strengthen security. As AI technologies continue to advance, communication networks will become more intelligent, adaptive, and resilient, paving the way for a highly connected and efficient digital future.

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11.0 Abbreviations

5G	: Fifth Generation
6G	: Sixth Generation
AI	: Artificial Intelligence
AIoT	: Artificial Intelligence Internet of Things
B2C	: Business-to-consumer
B5G	: Beyond 5G
BERT	: Bidirectional Encoder Representations from Transformers
CEM	: Customer Experience Management
CNNs	: Convolutional Neural Networks
CR	: Cognitive Radio
CSPs	: Communications Service Providers
CTCs	: Connectionist Temporal Classification
DAI	: Distributed Artificial Intelligence
DDOS	: Distributed Denial of Service
DL	: Deep Learning
DNN	: Deep Neural Network
DRL	: Deep Reinforcement Learning
EAs	: Evolutionary Algorithms
FOTA	: Firmware over the Air
GANs	: Generative Adversarial Networks
GAs	: Genetic Algorithms
GDPR	: General Data Protection Regulation
GEO	: Geostationary Orbit
HAPs	: High -Altitude platforms
IDS	: Intrusion Detection Systems
IoT	: Internet of Things
KPIs	: Key Performance Indicators
LEO	: Low Earth Orbit
LSTMs	: Long Short-Term Memory Networks
MEO	: Medium Earth Orbit
ML	: Machine Learning
MLPs	: Multilayer Perceptron
MPC	: Multi- Party Computation
NFV	: Network Function Virtualization
NLP	: Natural Language Processing
NLU	: Natural Language Understanding
OCR	: Optical Character Recognition
PSO	: Particle Swarm Optimization
QoE	: Quality of Experience
QoS	: Quality of Service
RF	: Radio Frequency
RL	: Reinforcement Learning
RNNs	: Recurrent Neural Networks
RPA	: Robotic Process Automation
SAGIN	: Space- Air- Ground Integrated Network
SDN	: Software Defined Networks

SLAs	: Service- Level Agreements
SOTA	: Software over the Air
SPA	: Shortest Path Algorithm
STT	: Speech- To- Text Transformers
TTS	: Text- To- Speech
TSP	: Telecom Service Provider
UAVs	: Unmanned Aerial Vehicles
UX	: User Experience
VUI	: Voice User Interface
XAI	: Explainable AI